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# **Antecedents of individual research performance of surgeons**

An empirical analysis of surgeons in US and German Academic Medical Centers

## **Dissertation**

Zur Erlangung der Würde des Doktors der  
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## **ABSTRACT**

Academic medical centers (AMCs) in many countries are faced with a difficult financial situation. Payers, such as health insurers and state institutions, frequently do not recognize that the organizational structure of AMCs differs from that of ordinary hospitals. Unlike other hospitals, AMCs are usually part of a university or medical school, and their mission is to combine patient care, education, and research, which can often lead to a trade-off between these three goals. In the attempt to find ways to resolve this issue, recent studies have shown that it might be beneficial for AMCs to respond to this situation with a strategic focus on research, which has been proven to increase the hospital's overall performance as well as clinical performance. In order to differentiate themselves from competitors and improve their performance, it therefore seems vital for AMCs to emphasize research programs and to encourage physicians in their research activities.

In the analysis of antecedents of medical research, however, most attention so far has been dedicated to the later stages of the new product development process, i.e. focusing on patents as indicators of inventions or the internal product development process in firms, despite the fact that significant components of medical research and development have their origins in hospitals. In contrast to other industries, the research activities of hospitals are not confined to special R&D departments, and can be seen as a bottom-up process where medical research is conducted at the level of individuals. Thus research performance depends to a large extent on the innovative capabilities and engagement of employees, which must be complemented and supported by an appropriate organizational context and managerial mechanisms. This dissertation therefore attempts to investigate the antecedents and underlying mechanisms of research performance of physicians in hospitals – specifically, surgeons in Academic Medical Centers (AMCs). The goal is to develop recommendations for AMC managers on how they can create and implement a work environment that stimulates the research performance of their physicians, which might in turn increase AMC performance.

Antecedents to individual research performance are assumed to be found at the individual, work team, and AMC level. The analysis is guided by theoretical models and approaches derived from organization and innovation research, such as the resource-based view, the diversity approach, and the ambidexterity hypothesis. The resource-based view is originally a theory of the firm, but can be a useful approach at the individual level, in particular in organizations such as universities, where performance can be traced back to individuals. The resource-based view thus serves as the conceptual basis for the assumption that access to various resource types leads to increased research performance.

Although numerous individual attributes and factors have been identified as potentially influential on individual research performance – such as age, gender, socioeconomic status, and educational background, along with several cultural and organizational dimensions – recent research has claimed that studies which only analyze the effects of individual factors without taking into account the team perspective and/or higher-level influences have limited capability to explain research performance. As a matter of fact, many organizations – including universities – have become more diverse in terms of demographic difference during the past two decades, and, consequently, groups within organizations have also become increasingly diverse. Team diversity is therefore assumed to be another important antecedent of individual research performance.

Finally, the ambidexterity hypothesis shifts attention to organizational-level influence factors. According to the ambidexterity hypothesis, it might be beneficial for firms and their employees to simultaneously pursue contradictory activities such as exploration and exploitation. Acting ambidextrously is especially relevant in AMCs, where physicians have to conduct research (exploration) along with patient care (exploitation). Although these activities should run alongside each other, the reality in AMCs is that one is often pursued at the expense of the other. The ambidexterity hypothesis therefore provides reason to believe that an ambidextrous hospital strategy might lead to an increase in individual performance. This proposition is extended to the individual level, assuming that individual ambidexterity leads to increased individual performance.

The empirical analysis is based on a data set of 10,380 surgeons in 50 US and 30 German AMCs, including data at each level. To avoid single source bias, subjective survey data is combined with objective data from external databases. The central analytical feature is multi-level regression analysis with up to three levels. Explanatory variables from the surgeon survey are generated using exploratory and confirmatory factor analysis. Explanatory variables at the team level related to team diversity are calculated using statistical indices such as the Gini index or standard deviation. Finally, data envelopment analysis is applied to determine hospital efficiency as an explanatory variable at the AMC level.

The results of the empirical analysis reveal that there are several factors at the individual, team, and organizational levels of analysis which fuel individual research performance. The impact of resource input varies according to resource type. While surgical research constantly benefits from individual resources, results also reveal that for the case of AMC resources some kind of saturation occurs. Network activity is only beneficial to research performance when it is intense and profound, while it hinders performance when activity is at a lower level. Furthermore, different forms of team diversity can affect individual research performance. Team diversity in hierarchy decreases research performance, while team diversity in education, additional qualifications, and in performance stimulates individual research performance. Finally, the results suggest that ambidexterity at the individual as well as at the organizational level positively affects individual performance. In addition, several important moderating factors on the relationship between ambidexterity and performance were identified. Organizational coordination and mobilization mechanisms such as incentives and R&D process formalization can be effective mechanisms to direct attention to research when organizations have a clear focus on exploration or exploitation, but are less effective in more complex ambidextrous environments. Access to internal resources such as money and time is beneficial to the research performance of ambidextrous surgeons, while access to external resources such as intense network activity impedes the research performance of surgeons who act ambidextrously.

Managers of AMCs who aim to create a research-friendly environment should therefore pursue a comprehensive approach in consideration of individual-, team-, and organizational-level influence

factors when implementing processes and strategies that aim to stimulate the research performance of their physicians. The antecedents identified in the present analysis might serve as a guideline and reference point regarding this approach.



## **CHAPTER 1: Synopsis**

**PRELIMINARY WORK: RESEARCH IN ACADEMIC MEDICAL CENTERS**

In many countries, academic medical centers (AMCs) are faced with a difficult financial situation. They usually receive reimbursement for the delivery of health care in amounts that are similar to that received by nonteaching hospitals. But payers, such as health insurers and state institutions, frequently do not recognize that the organizational structure of AMCs differs from that of ordinary hospitals due to the former's role as multiservice organizations. Unlike other hospitals, AMCs are usually part of a university or medical school, and their mission is to combine patient care, education, and research, which can often lead to a trade-off between these three goals. Good residency training means more intensive patient contact, which, however, can also slow down care processes and research. On the other hand, if physicians focus too intently on patient care, they may not have enough time to interact with students or pursue research. In this sense, patient care, education, and research can come into conflict with each other, reducing the performance of AMCs compared with ordinary hospitals. AMCs have to respond to this dilemma and need to identify the appropriate strategies to cope with this specific triad of duties.

Based on a sample of 24 German AMCs, Chapter 2 of this dissertation provides an empirical analysis of how different AMC strategies impact overall AMC performance, as well as their performance in the delivery of patient care. Performance measures were determined via data envelopment analysis (DEA). Using the framework of strategic groups and cluster analysis, two strategic groups were identified: one that – besides its clinical duties – specializes on teaching, vs. another that specializes in research. Controlling for several other structural variables (e.g. hospital size, location, grants), our results reveal that membership of the research group leads to better overall performance and better performance in the delivery of patient care.

This finding – that a research specialization among AMCs leads to higher overall performance – has not been identified elsewhere. An important question arising from this is whether these results can be generalized beyond AMCs – that is, whether other hospitals can also increase their performance by initiating research programs. However, for the case of AMCs it therefore seems

vital to emphasize research efforts and programs and to encourage physicians in their research activities. This conclusion gave birth to the actual goal and concept of this dissertation.

## **GOALS OF THIS DISSERTATION**

From other industries we know that a steady stream of novel products, services, or processes is widely assumed to be a key marker of superior organizational performance and long-term survival (e.g. Jansen et al. 2006). While this could be said for nearly any industry, it is particularly true in fast-growing and research-intensive industries such as the health care sector, which is confronted by a staggering array of complex challenges, including ongoing pressures for health care reform, new diagnostic and treatment technologies, and the emergence of new organizational forms (Short et al. 2002). Recent studies in hospital settings have also shown that medical research in hospitals increases overall performance (Schreyoegg and von Reitzenstein 2008) as well as clinical performance (Salge and Vera 2009).

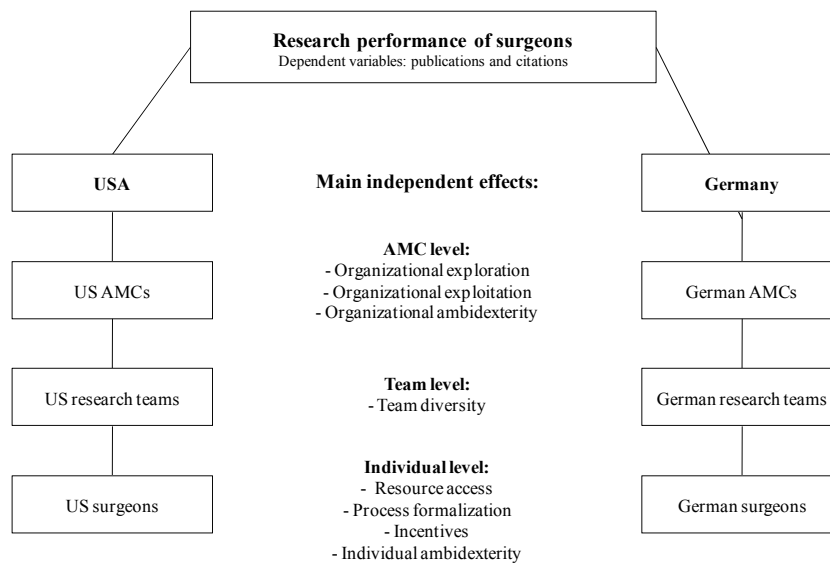
As a matter of fact, a significant part of medical technology research and development has its origin in hospitals. However, in the analysis of medical research, i.e. medical devices or pharmaceuticals, most attention has been so far dedicated to the later stages of the new product development process – i.e. focusing on patents as indicators of inventions or the internal product development process in firms. In contrast to other industries, the research activities of hospitals are not confined to special R&D departments, and can be seen as a bottom-up process where medical research is conducted at the level of individuals. Thus hospitals' research performance depends to a large extent on the innovative capabilities and engagement of their employees, which must be complemented and supported by an appropriate organizational context and managerial mechanisms. In spite of the relevance of the research activities of hospital employees, relatively few studies analyze individual and organizational drivers of research conducted by physicians in hospitals (e.g. Lettl et al. 2008; Lüthje 2003). Thus the aim of this dissertation is to investigate the antecedents and underlying mechanisms of research performance of physicians in hospitals, specifically surgeons in AMCs, and at various levels of analysis. This dissertation thereby attempts

to develop recommendations for AMC managers on how they can create and implement a work environment that stimulates the research performance of their physicians, which might in turn increase AMC performance.

## **CONCEPTUAL APPROACH, DATA, AND METHODS**

According to recent management research, antecedents of innovation and research performance can be found at multiple levels of analysis (Gupta et al. 2007); this is especially the case for analysis which focuses on individual research performance – such as in the present dissertation. Individual research performance might not only be driven by individual capabilities or motives, but also by influence factors at higher levels of analysis such as the team or organizational level. Consequently, the central analytical feature of this dissertation is multi-level analysis, which is applied to explore the individual research performance of physicians and the influence exerted upon it by factors at individual, team, and organizational (AMC) levels of analysis. Empirical analysis is guided by theoretical models and approaches derived from organization and innovation research, such as the resource-based view, the diversity approach, and the ambidexterity hypothesis. The resource-based view is originally a theory of the firm but can also be a useful theoretical foundation at the individual level, in particular in organizations such as universities where performance can be traced back to individuals. The team diversity approach assumes that diversity of various kinds in the composition of work teams can affect performance both positively and negatively, depending on the contextual setting. Finally, the ambidexterity hypothesis proposes that it might be beneficial for firms and their employees to simultaneously pursue contradictory activities such as exploration and exploitation.

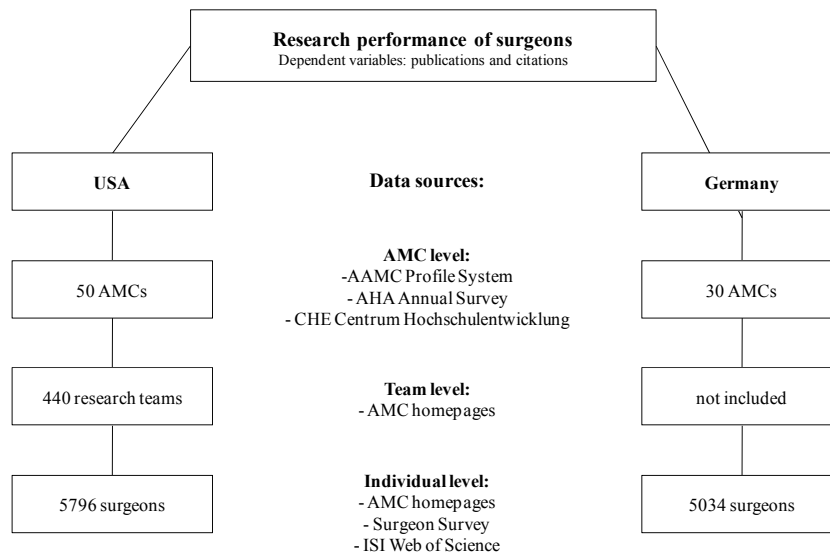
Figure 1. Study design



As it would have been unrealistic to collect data on all medical subspecialties, this research chose surgeons as an example. This was for a number of reasons: First, surgeons are the largest group of physicians in AMCs. Second, even though there are a number of surgical sub-specialties, their day-to-day business is homogeneous: all of them have to fulfill their duties in patient care, at the bedside, in teaching and research, and – in contrast to other physicians – in the operating room. Third, surgical research involves product-related as well as process-related research. This may allow generalizability to other areas in which research is conducted. Finally, Germany and the USA were chosen as examples of two countries leading in terms of medical care and medical research. The analysis is therefore based on a dataset from surgeons in US and German AMCs, with data at individual, team, and organizational levels of analysis, combining subjective self-generated survey data with objective data sources from external databases. At the individual level we surveyed 659 surgeons in 18 US and 20 German AMCs and collected research performance and curricular data about 10,380 surgeons (including the surveyed surgeons) in 50 US and 30 German AMCs from AMC homepages and the ISI Web of Science database. On a team level, 5,796 US surgeons were assigned to 440 research teams for which team-level variables were identified with data from AMC homepages. Finally, on an organizational level, we gathered AMC performance data, e.g. hospital costs, case-mix, and labor data from external databases like the Annual Survey of the American

Hospital Association, the American Association of American Medical Schools Profile System, or the German Centrum für Hochschulentwicklung (see figure 2).

Figure 2. Data sources



The empirical analysis is based on the assumption that the research performance of surgeons is a function of individual surgeon characteristics, team-level measures, and contextual factors at the AMC level. Therefore the main analytical instrument is multi-level regression analysis with up to three levels, nesting surgeons as micro units within research teams, and research teams within AMCs. Both research team and AMC levels were considered to be macro units. Explanatory variables from the surgeon survey are generated using exploratory and confirmatory factor analysis. Explanatory variables at the team level are calculated using statistical indices such as the Gini index or standard deviation. Finally, data envelopment analysis is applied to determine hospital efficiency as an explanatory variable at the AMC level.

In some of the following chapters other terminologies for individual research performance and AMCs have been used. This had to do with the specific research question, the relevant theoretical framework, and the journal to which the papers have been submitted. Specifically, we have utilized the terms *individual research productivity* and *individual(-level) R&D performance* as synonyms

for research performance, and the term *medical school* as a synonym for AMC. They can be understood in an analogous manner.

## **INDIVIDUAL RESEARCH PERFORMANCE AND RESOURCE INPUT**

Due to the central role resources play as critical drivers of individual research performance (e.g. Lettl et al. 2008), Chapter 3 focuses on the impact of different resource types on individual research performance. The conceptual framework of the analysis is based on the theory of the resource-based view (RBV), which has emerged as a very popular theoretical perspective for explaining performance and has already been applied in hospital settings (e.g. Short et al. 2002). Historically, scholars have used “resources” as a general term to refer to inputs into organizational processes (Barney 1991). The RBV is originally a theory of the firm but recent theoretical and empirical research shows that antecedents to competitive advantage and firm performance can be found not only at the firm level but also at individual or network levels (Eisenhardt and Martin 2000; Rothaermel and Hess 2007). Consequently, the RBV has lately also served as a theoretical foundation for the analysis of individual performance (e.g. van Rijnsoever et al. 2008).

We follow the idea that relevant resources can be found on an individual level (e.g. competences and experience), may be provided by the hospital (e.g. time, funding, or top management support), and can be accessed through external networks resources (e.g. research contacts). Our aim is to determine how these various resource types impact the research performance of surgeons. We further hypothesize that resources are important for research performance but that resource access will not be valuable in every situation. In other words, we assume that a point will be reached beyond which an increase in resource input will not yield performance improvement.

Our empirical analysis showed that the research performance of surgeons is indeed strongly dependent on the resources they had access to. In other words, research performance is dependent on a set of attributes such as individual technological skills, tangible resources such as technological equipment, and lastly the opportunity to gather inspiration and ideas through external communities and cooperation. Nevertheless, we could also show that the actual impact and form of

relationship varies according to resource type. While surgical research constantly benefits from individual resources, our results also reveal that for the case of AMC resources some kind of saturation occurs. If a certain resource level is reached, additional resources will reduce research performance. Network activity is instead only beneficial to research performance when it is intense and profound, while it hinders performance when activity is at a lower level. Consequently, the deployment of individual, AMC, and network resources has to be differentiated according to resource type.

### **INDIVIDUAL RESEARCH PERFORMANCE AND TEAM DIVERSITY**

Numerous studies have examined the effects of individual attributes and factors on individual research performance, including age, gender, socioeconomic status, and educational background (Braxton and Bayer 1986; Hall et al. 2007; Levin and Stephan 1989; Stephan 1998; Tien and Blackburn 1996), along with several cultural and organizational dimensions (Conrad and Blackburn 1986). However, Stephan (1996) emphasizes that studies which only analyze the effect of individual factors without taking into account the team perspective and/or higher-level influences have limited capability to explain research performance, as in many fields research is conducted in groups of individuals rather than by an individual alone.

As a matter of fact, organizations are increasingly adopting work-group compositions that incorporate differences in functional or educational background, such as cross-functional and interdisciplinary project teams (van Knippenberg and Schippers 2007). Organizations – including universities – have also become more diverse in terms of demographic differences during the past two decades and consequently the groups in organizations have also become increasingly diverse (Jackson et al. 2003; Williams and O'Reilly 1998). Research in the area of work team diversity has therefore also grown. Still, several comprehensive reviews have noted that the findings do not provide a clear consensus regarding the performance effects of work team diversity (Harrison and Klein 2007; Jackson et al. 2003; Milliken and Martins 1996; van Knippenberg and Schippers 2007; Williams and O'Reilly 1998). Recent research has therefore suggested that contextual factors at



multiple levels of analysis influence and moderate the performance outcomes of diversity in teams (Bamberger 2008; Johns 2006; Joshi and Roh 2009; Rousseau and Fried 2001).

Chapter 4 of this dissertation therefore aims to analyze the effect of team diversity on individual research performance, while controlling for factors influencing research performance at the individual and AMC level. Building on diversity theory, we distinguish between disparity (e.g. gender and hierarchy diversity) and variety aspects of diversity (e.g. diversity in educational background, performance, experience, and nationality), and hypothesize that the former – diversity as disparity – negatively influences performance, while diversity as variety positively influences performance. Both hypotheses were supported by our data. Diversity in hierarchy decreases research performance while diversity in educational background, additional qualifications, and in performance stimulates research performance. Diversity in experience, in gender, and in nationality had no significant influence on research performance.

## **INDIVIDUAL RESEARCH PERFORMANCE AND ORGANIZATIONAL AMBIDEXTERITY**

Having analyzed individual and team-level factors in the previous chapters, Chapter 5 shifts attention to organizational-level influence factors on individual research performance. Theorists and practitioners are still struggling to understand how organizations can best mobilize and coordinate exploratory activities while addressing exploitative operational requirements. The need to focus on both exploration and exploitation – in short, on ambidexterity – is widely recognized as a prerequisite for long-term success, and an increasing number of studies are examining the underlying organizational factors of ambidexterity and its impact on organizational performance. Although several seminal works on exploration, exploitation, and ambidexterity have been published to date, empirical findings addressing the effects of such different organizational foci remain scarce (Groysberg and Lee 2009; He and Wong 2004; Mom et al. 2009). More specifically, there is an ongoing debate in the literature about whether ambidexterity undermines or enhances the generation of knowledge by employees (Adler et al. 1999). Unlike most of the more macro-

level research on organizational ambidexterity, this debate assumes that individual-level outcomes are related to organizational factors. With this in mind, we take a multi-level approach in our study, aiming to deepen the understanding of organizational foci and their impact on individual-level exploratory activities, including research performance in particular.

Several researchers on ambidexterity have shown that traditional organizational incentives and processes support exploitative activities at the expense of exploratory goals. To succeed, they argue, ambidextrous organizations require mechanisms designed to mobilize and coordinate exploratory activities (Jansen et al. 2006), such as incentives and parallel processes. Although mechanisms like these are implemented at the organizational level, they usually influence behavior at the level of individual employees.

Suggesting the presence of moderation effects across levels, we hypothesize that the impact of mobilization and coordination mechanisms on the research performance of individual employees varies according to organizational focus (exploration, exploitation, and ambidexterity). Our results show that mobilization and coordination mechanisms can benefit research performance in some environments but hinder it in others. The results also suggest that these mechanisms are less effective in more complex environments, such as ambidextrous organizations. We conclude that mobilization and coordination mechanisms can shift objectives towards a desired goal but must be deployed carefully while taking organizational focus into account.

## **INDIVIDUAL RESEARCH PERFORMANCE AND INDIVIDUAL AMBIDEXTERITY**

Existing research on the exploration–exploitation trade-off has thus far been mainly focused on organizational-level processes, scarcely taking into account the individual level. In most of the studies, the tensions that ambidexterity creates are resolved at an organizational level. In sum, research has suggested that structural mechanisms are used to enable ambidexterity, whereas most individuals are seen as focused on either exploration or exploitation activities. Some studies on structural ambidexterity acknowledge that a few people at higher organizational levels need to act ambidextrously by integrating exploitative and explorative activities (e.g. Smith and Tushman

2005). However, the individual dimension of ambidexterity is not explored further (Raisch et al. 2009). It is only recently that some studies have attempted to take a step toward filling this gap empirically (Audia and Goncalo 2007; Groysberg and Lee 2009; Mom et al. 2009). Although these studies deliver valuable insights into the nature and underlying mechanisms of individual ambidexterity and lay the foundations for future research, three important aspects of individual ambidexterity remain unaddressed: First, no empirical analysis investigates ambidexterity at the R&D employee- (not managerial) level; second, the performance implications of individual ambidexterity have not been determined; third, and consequently, no conclusions about antecedents of the individual ambidexterity–performance relation can be drawn.

Chapter 6, the final chapter of this dissertation, attempts to close this research gap by means of a conceptualization of individual ambidexterity, extending the organizational ambidexterity model from the previous chapter. A first analytical step analyzes the impact of individual-level ambidexterity on individual research performance while controlling for organizational ambidexterity; a second step further investigates the moderation effect that resource access exerts on this individual-level ambidexterity–performance relation. Internal (i.e. firm) and external (i.e. network) resources are thereby distinguished.

Individual ambidexterity is assumed to positively affect individual research performance. Further, internal resource access is assumed to positively moderate this relation while external resource access is assumed to have a negative impact on the individual ambidexterity–performance relation. The results support these hypotheses. I conclude that managers should ensure that the creative workforce acts ambidextrously, and thus is not only engaged with explorative tasks but also involved in exploitative activities. Furthermore, managers should make sure that the appropriate resources are provided to individuals who attempt to combine exploration and exploitation.

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## **CHAPTER 2: Strategic groups and performance differences among academic medical centers.**

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# Strategic groups and performance differences among academic medical centers

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**Background:** The performance of academic medical centers (AMCs) differs from that of other hospitals because AMCs must combine the delivery of patient care with teaching and research.

**Purpose:** This study investigates the effects of strategic group membership as opposed to other structural determinants on the performance of AMCs.

**Methodology:** We used data from 24 German AMCs and applied data envelopment analysis with superefficiency to measure the performance of AMCs by considering AMC-specific inputs and outputs for patient care, teaching, and research. We used cluster analysis to identify strategic groups and applied regression analysis to explore their impact on performance.

**Results:** Our results reveal two strategic groups based on a specialization either in teaching or in research. The strategic group that specialized in research showed significantly better performance; structural variables did not play a major role.

**Practice Implications:** The results provide an important justification for managers to develop suitable strategic concepts for AMCs. If low organizational efficiency is detected, managers need to consider analyzing whether their AMC belongs to an appropriate strategic group. An emphasis on research may increase overall efficiency.

In many countries around the world, academic medical centers (AMCs) are faced with a difficult financial situation. They usually receive reimbursement for the delivery of health care in an amount similar with that received by nonteaching hospitals.

**Key words:** academic medical centers, data envelopment analysis, strategic groups, teaching hospitals

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Although they are compensated for their teaching workload, special case mix, or research activities, this compensation is often too low (Linna & Häkkinen, 2006; Lopez-Casanovas & Saez, 1999). Payers, such as health insurers and state institutions, frequently do not recognize that the organizational structure of AMCs differs from that of ordinary hospitals due to the former's role as multiservice organizations. Unlike other hospitals with teaching status, AMCs are usually part of a university or medical school, and their mission is to combine patient care, education, and research, which can often lead to a trade-off between these three goals. Good residency training means more intensive patient contact, which, however, can also slow down care processes and research. On the other hand, if physicians focus too intently on patient care, they may not have enough time to interact with students or pursue research. In this sense, patient care, education, and research can come into conflict with each other, reducing the performance of AMCs compared with ordinary hospitals.

Only few studies have been conducted to date on the performance of AMCs or teaching hospitals in general. These studies defined performance in different ways. One group of studies defined performance as clinical measures such as mortality, adverse events, or other measures for quality of care. The results of these studies suggest that performance in teaching hospitals is higher than in nonteaching hospitals (Ayanian, Weissman, Chasan-Taber, & Epstein, 1998; Brennan et al., 1991; Hartz et al., 1989; Keeler et al., 1992; Kuhn, Hartz, Gottlieb, & Rimm, 1991; Rosenthal, Harper, Quinn, & Cooper, 1997; Taylor, Whellan, & Sloan, 1999). The other group of studies defined performance as economic measures such as costs or efficiency frontiers based on costs. These articles suggest that nonteaching hospitals perform better than teaching hospitals. For a sample of U.S. hospitals, Grosskopf, Margaritis, and Valmanis (2001) were able to show that only 10% of teaching hospitals can effectively compete with nonteaching hospitals based on the provision of patient services. Moreover, Mechanic, Coleman, and Dobson (1998) found that costs per case were 44% higher for AMCs than for other teaching hospitals after adjusting for case mix, wage levels, and direct graduate medical education. This finding was confirmed by another study that focused only on teaching hospitals and showed that hospitals with smaller teaching loads performed better than AMCs (Rosko, 2004). This article follows a similar approach as the latter group of studies and defines performance as efficiency scores from data envelopment analysis (DEA) generated from inputs and outputs.

Previous studies suggest that it is difficult to adjust for structural factors that contribute to performance differences when comparing AMCs, teaching hospitals with smaller teaching loads, and nonteaching hospitals. In particular, indirect teaching costs are difficult to measure and represent a cost-increasing factor for teaching hospitals, which may be caused by unmeasured differences in case mix (Custer & Wilke, 1991). These findings suggest that, when measuring hospital performance, AMCs should be treated as a separate group and examined using different variables. However, only one study to date has concentrated solely on the performance of AMCs. Fisher, Wennberg, Stukel, & Gottlieb. (2004) revealed considerable differences among AMCs in the quality of care provided to patients. This study investigates the performance of AMCs using the concept of strategic groups. The framework of strategic groups is used to explain how strategic choice, as opposed to structural factors, influences the performance of AMCs.

### **Theoretical Framework**

Although the concept of strategic groups originated with Hunt (1972), it is usually associated with Porter (1979). Porter argues that, in one industry, firms with similar

assets pursue similar strategies with similar performance results in ways that cannot be explained by the structure–conduct–performance paradigm. Strategic variables such as marketing methods and the use of certain technologies can create effective mobility barriers. These barriers protect each strategic group from outside competition and may lead to performance differences (Osborne, Stubbart, & Ramaprasad, 2001; Short, Ketchen, Palmer & Hult, 2007; Tywoniak, Galvin, & Davies, 2007). McGee (2003) differentiates between market-related barriers (e.g., advertising, sales-force size, and breadth of product line) and asset-related barriers (e.g., product patents). Strategic groups only develop if mobility barriers (a) cannot be removed easily and (b) require certain investments often associated with sunk costs. Thus, high-performance firms have an incentive to establish barriers to prevent other firms from entering their domain.

Since the late 1970s, many empirical studies on different industries have been performed based on this concept. Many of these studies have chosen the pharmaceutical industry as their focus due to its heterogeneous market structure (Bogner, Thomas, & McGee, 1996; Leask & Parker, 2007; Mehra & Floyd, 1998). Few studies have investigated strategic groups in hospitals and health care providers, and in those that have investigated these groups, the empirical results have been mixed. Some studies found evidence supporting the existence of strategic groups (Ketchen, Thomas, & Snow, 1993; Madorran García & de Val Pardo, 2004; Marlin, Lamont, & Hoffman, 1994; Short, Palmer, & Ketchen, 2002), but other studies did not (Nath & Gruca, 1997). The concept has not been applied yet to AMCs, although the heterogeneity of the AMC market would seem to be fertile ground for its application. Warning (2004) applied the concept to universities investigating the link between performance and specialization in research or teaching. Our approach builds on concepts previously employed in strategic-group research conducted, in particular, in the realm of hospitals and institutions of higher education.

We assumed that AMCs might define different strategies to compete on the market for AMC services, much like organizations in other industries. As AMCs usually serve as tertiary hospitals, patient selection is less likely than in other hospitals. Consequentially, the case mix is likely to be influenced by structural factors rather than management strategies. We assumed that AMCs differentiate from each other by specializing in teaching or research. Clearly, a focus on research can be rewarding for an AMC, for example, due to improved possibilities to acquire research grants. However, we also assume that, similar with teaching universities in other academic disciplines (e.g., education), there are also AMCs focusing on teaching. These AMCs excel by providing ideal conditions for students to pass the Medical Licensing



Examination and other standardized examinations which may increase their number of graduates and again attract more and better students. This may increase revenues through tuition fees or public funding.

Mobility barriers are more likely to be present in research than teaching as the former requires more specific human capital than the latter. Research is also more likely to require investments in assets, leading to sunk costs such as specialized equipment for clinical trials or laboratories. Thus, we also assumed that an increase in research output is more costly than an increase in the number of graduates. This led to our first hypothesis:

*Hypothesis 1:* Membership in a strategic group that specializes in research rather than in teaching is associated with higher overall performance.

Moreover, strong capabilities in research may also lead to higher performance in the delivery of patient care. Especially because AMCs often cater to patients with severe conditions requiring complex treatment decisions, cutting-edge knowledge could facilitate patient care processes. Formally stated,

*Hypothesis 2:* Membership in a strategic group that specializes in research rather than in teaching is associated with higher performance in the delivery of patient care.

### **Research Design and Methods**

**Setting and data.** Our study is based on cross-sectional data for German AMCs for the fiscal years 2002–2004. AMCs in Germany usually belong to the medical faculty of a public university, and the hospital is a fully integrated part of the medical faculty. There are also other teaching hospitals affiliated with medical faculties in Germany, but these offer much smaller teaching programs and were therefore not considered in this study. Most AMCs included were located in disparate geographic regions, but the environment in terms of funding was comparable. The criteria for being recognized as an AMC in Germany are similar with those found in Stark Rule's definition of AMCs in the United States. In 2004, diagnosis-related groups were introduced in all hospitals in Germany except for specialized psychiatric centers. AMCs are reimbursed using the same diagnosis-related group rate applied to all other hospitals. In addition, they receive limited reimbursement for heavy teaching loads and other circumstances (Schreyögg, Tiemann, & Busse, 2006). As a result, competitive pressure has increased considerably for AMCs in Germany and is comparable to the situation seen in the U.S. hospital sector.

Our primary sources of data on patient care and teaching programs were the annual reports published by the hospitals and the budget reports published by the

respective state ministries. If neither was available, we sent a request for the data to the hospitals or state ministries directly. Data on patient care and teaching programs were for the fiscal year 2004. Data on research, that is, publications and inventions, were obtained from the Centrum fuer Hochschulentwicklung (CHE) report (CHE Centrum fuer Hochschulentwicklung, 2006), a detailed ranking of German institutions of higher education, and were for the years 2002–2004. There were 33 AMCs in Germany in 2004, not counting certain exceptional cases, such as medical faculties with shared hospitals. Of these 33 AMCs, several were excluded because their structure differed considerably and several hospitals did not report any data. Ultimately, we were able to include 24 AMCs in the study.

### **Measuring Performance Using Data Envelopment Analysis**

As mentioned previously, only one empirical study has measured the performance of AMCs to date. Earlier research on strategic management, health care organization, and institutions of higher education has advocated the use of multiple measures of organizational performance. In the case of AMCs, this seems even more necessary considering the highly complex system of goals with which these institutions are faced. Because AMCs are often public or not-for-profit entities, standard performance measures such as return on investment and profitability seem inappropriate. In this situation, performance is commonly measured by estimating efficiency scores using data envelopment analysis (Hao & Pegels, 1994; Harrison, Coppola, & Wakefield, 2004). Data envelopment analysis is a mathematical linear programming technique for evaluating the relative efficiency of organizations. It uses the ratio of weighted outputs to weighted inputs to determine relative efficiency, whereby the weights are not preassigned but rather determined by the model, thus avoiding any bias of subjectively assigned weights. The model constructs a piecewise linear frontier that envelops the inefficient units. It measures inefficiency as the radial distance from the inefficient unit to the frontier and produces an efficiency score reflecting the relative efficiency of each unit (Cooper, Li, Seiford, & Zhu, 2004). DEA allows the simultaneous consideration of multiple inputs and outputs, which seems particularly well-suited for measuring the performance of AMCs.

A drawback to the traditional DEA approach is that the number of inputs and outputs is limited by the sample size. If the number of inputs and outputs is too large in relation to the sample size, the efficiency score of a substantial number of units will be equal to 1, which only qualifies these units as efficient but does not allow for any further differentiation among the efficient units.

This especially creates problems when DEA scores are used as dependent variable for regression analysis in a second step as it does not ensure effective variation between the units. To cope with this problem, we used the concept of superefficiency, which is an extension of the traditional DEA approach and which is particularly recommended in case of small samples (Andersen & Petersen, 1993). Superefficiency indicates the extent to which an efficient unit exceeds the frontier formed by other efficient units. Thus, the concept of superefficiency allows for efficiency scores beyond 1 and for assigning a clear value to each efficient unit. The concept of superefficiency and its applications in the context of hospitals have been described in detail by Vera and Kuntz (2007).

In selecting inputs and outputs, we followed the example of other studies that had developed DEA frameworks for measuring the efficiency of teaching and nonteaching hospitals (Grosskopf, Margaritis, & Valmanis, 2001; Lehner & Burgess, 1995; Jacobs, Smith & Street, 2006) and institutions of higher education (Thursby, 2000; Avkiran, 2001; Warning, 2004). For the purposes of our study, we chose three inputs. The first input variable (SUPPLIES) was the amount spent on supplies including operational expenses but excluding payroll, capital, and depreciation expenses (in 100 million Euro). Additional input variables were the number of medical and nonmedical staff measured as a staff index (STAFF) and the number of academic staff weighted by their salaries (ACAD). For generating the staff index, we aggregated the number of full-time equivalent physicians, nurses, and other staff members. Each of the three groups was weighted by the average salary the group received in 2004 according to the German pay scale for public employees (BAT). Although not all AMCs pay their employees according to this pay scale any longer, it is a good approximation of the average salary in each group. Here, it is also important to note that, according to this pay scale, there are still differences in salaries between East and West Germany; we also took these differences into account. Similarly, the academic staff variable was created by taking the German pay scale for public servants into account. We originally intended to include beds as an additional input that would have served as a proxy for capital expenses. However, when testing correlations between input variables using the Bravais–Pearson correlation coefficient, it turned out that the number of beds was correlated with the STAFF variable. To avoid a biased DEA specification (Jacobs et al., 2006), we decided to refrain from using the number of beds as an input variable for the DEA model and to use it, instead, as a control variable at a later stage of the analysis. Correlations between the remaining three input variables were either low or moderate.

To measure the output of AMCs, we considered five output variables. Including the number of inpatient and

outpatient cases is generally recommended to measure patient care output (Jacobs et al., 2006). The first output variable, INPATIENT, reflects the inpatient case mix of each hospital. All hospitals in Germany use the same methodology to determine the case mix as defined by the German diagnosis-related groups. The second output variable, OUTPATIENT, is the number of outpatient visits, including outpatient surgeries and emergency room visits. Currently, the data available for outpatient cases do not allow adjustment for severity; we, therefore, included the unadjusted number of outpatient visits as an output variable. To measure the teaching output, the number of graduates is a generally accepted output measure in the literature (Avkiran, 2001; Warning, 2004). Therefore, we constructed an index that reflects the number of persons who passed medical-related degrees of different levels (EDUCATION). Whereas graduate, postgraduate, and doctoral degrees were counted as one point each, passing the so-called *Habilitation*—a German postdoctoral degree required to qualify for professorship positions—was counted as three points. Most examinations are standardized throughout Germany and are therefore comparable between different sites. The number of publications listed in the Science Citation Index is commonly used as a measure of the research output of higher education institutions (Thursby, 2000; Warning, 2004). We thus included an output variable called PUBLICATIONS, which consisted of the number of publications each AMC had in the Science Citation Index (i.e., as a proxy for quantity) multiplied by the number of times each publication was cited (i.e., as a measure of quality). However, the field of medical research is driven not only by publications but also by inventions; because of this, we also included the number of inventions registered in the official patent register as a fifth output variable (INVENTIONS).

A descriptive overview of the inputs and outputs used for our DEA model is given in Table 1. These reveal large variations between AMCs.

First, we ran a full DEA model with all of the inputs and outputs defined above. To investigate the impact that alterations to the model specifications would have on how the AMCs compared with each other and to allow for the analysis of partial performance (e.g., performance of patient care), we created four additional DEA models. The specifications of all five models are summarized in Table 2.

### **Strategic Group Measures and Clustering Procedure**

Cluster analysis is a common way to identify strategic group structures. To identify possible strategic groups, we proceeded in three steps to increase the validity of

**Table 1**

## Descriptive overview of aggregated inputs and outputs used for DEA

	<i>M</i>	<i>SD</i>	Minimum	Maximum
<b>Inputs</b>				
SUPPLY	120	65	25	314
STAFF	3,344	1,345	1,682	7,618
ACAD	105	44	52	248
<b>Outputs</b>				
OUTPATIENT	263,817	198,636	40,000	900,000
INPATIENT	70,847	29,774	34,286	165,066
EDUCATION	612	389	132	2,052
PUBLICATIONS	3,884	2,773	845	13,589
INVENTIONS	20	4	3	43

the cluster. First, we defined variables that most likely reflected an AMC's emphasis on either research or teaching. Studies of higher education institutions have suggested that the realized publication:graduate ratio is a suitable variable for clustering (Warning, 2004). Thus, we also included this variable in this study and added the realized invention:graduate ratio as a second variable. To prevent these variables from acting in concert in our analysis and possibly leading to erroneous clusters (Ketchen et al., 1993), we tested for multicollinearity, which we, however, did not detect. Second, we used Ward's approach—a hierarchical clustering method—as a guide to estimate the number of clusters present in the data as well as squared Euclidean distance to calculate proximities between variables. Third, we performed a *K* means analysis—a form of nonhierarchical cluster analysis—to test the validity of the results. *K* means analysis has the ability to reassign members to certain clusters using the results of Ward's method as a starting point (Ketchen & Shook, 1996).

### Hypothesis Testing

After identifying valid clusters, we performed an OLS regression analysis to assess whether membership in the

defined groups led to differences in performance. Although most studies use variance analysis to test for the existence of strategic groups, we applied regression analysis and considered a number of control variables in addition to a dummy variable for group membership. The use of control variables is particularly important in the health care context because there are usually certain structural or regulatory determinants of hospital performance that a hospital cannot fully influence. The first control variable was the number of licensed and staffed beds (BEDS), which served as a proxy for capital (Harrison et al., 2004). We also used the case mix index (CMI) as a proxy for the overall severity of treated cases. The amount of research grants acquired (GRANTS) was included as grants lead to increased input and might thus reduce performance. Finally, we included a dummy variable (URBAN) that differentiated between urban and rural location. A hospital located in a metropolitan area with population of at least 200,000 was characterized as an urban hospital and received a value of 1 for the dummy urban variable. This dummy variable was included to control for local differences in the levels of wages for staff belonging to groups other than those included in our staff index (e.g., support staff). However, as suggested by Warning (2004), urban location can also

**Table 2**

## Specification of DEA models

	Inputs	Outputs
Full model	STAFF, SUPPLY, ACAD	INPATIENT, OUTPATIENT, EDUCATION, PUBLICATIONS, INVENTIONS
Full model without inventions	STAFF, SUPPLY, ACAD	INPATIENT, OUTPATIENT, EDUCATION, PUBLICATIONS
Patient care model	STAFF, SUPPLY	INPATIENT, OUTPATIENT
Research model	STAFF, SUPPLY, ACAD	PUBLICATIONS, INVENTIONS
Teaching model	ACAD	EDUCATION

**Table 3**

## Correlation matrix of efficiency scores for different models

	Teaching model	Patient care model	Research model	Full model (without inventions)	Full model
Teaching model	1.00	–	–	–	–
Patient care model	–.43	1.00	–	–	–
Research model	.51	.05	1.00	–	–
Full model (without inventions)	.05	.05	.35	1.00	–
Full model	.07	.70	.41	.97	1.00

indicate that urban AMCs face higher demand by students, researchers, and patients and therefore have fewer incentives to increase performance to attract these groups. We performed three regression models using the DEA superefficiency scores from three different DEA specifications as dependent variables.

## Results

A correlation matrix with the efficiency scores of individual AMCs for the five models is presented in Table 3. Our results suggest that there was a moderate negative correlation between teaching and patient care, which indicates a substitutional relationship. However, we were unable to find a substitutional relationship between teaching and research. Including inventions as an output variable clearly did not have a major effect on the results because the correlation between the full model and the full model without inventions is very high. The correlation matrix indicates that, although patient care efficiency dominates overall efficiency, the inclusion of additional variables (i.e., compared with the patient care model) has an important effect on the model's comprehensiveness.

The cluster analysis identified two strategic groups based on the definition of our variables. The first group consisted of AMCs specializing in research, whereas the

second group consisted of AMCs specializing in teaching. Analysis of variance supported the existence of strategic groups because significant differences were detected between the groups for both defining variables ( $p < .01$ ). Table 4 displays the mean and standard deviation for the variables used to determine strategic groups and for the variables used in the regression analysis. The table also reveals that throughout the three models efficiency scores are higher for the group specializing in research. In general, the mean scores are higher for the full model than for the patient care model because the full model contains more inputs and outputs.

Table 5 summarizes the regression results for the three regression models. Throughout the models, group membership was coded as a dummy variable (research group = 1; teaching group = 0). Regressions with efficiency scores for the full model and the full model without inventions showed that group membership had a significant impact on the overall performance of AMCs—a finding that supports our first hypothesis. However, the relationship was weaker for the model without inventions ( $p < .05$ ) than it was for the full model ( $p < .01$ ). In both models, the control variables had only a minor impact on performance. The regression with the patient care model also revealed a significant relationship between group membership and performance of patient care, a finding that supports our

**Table 4**

## Characteristics of strategic groups

	Beds	CMI	Grants	Urban	Full model	Full model (without inventions)	Patient care model	Publications: Graduates	Inventions: Graduates
Research group ( $n = 9$ )									
<i>M</i>	1,053.77	1.32	37.11	0.67	1.27	1.22	0.95	2.96	0.04
<i>SD</i>	533.12	0.11	27.68	0.05	0.25	0.24	0.17	1.12	0.01
Teaching group ( $n = 15$ )									
<i>M</i>	774.47	1.29	22.47	0.53	1.01	1.00	0.67	1.96	0.02
<i>SD</i>	203.45	0.12	9.45	0.52	0.16	0.15	0.21	0.47	0.01

Note. CMI = case mix index.

Table 5

## Regression results for each model

	Full model	Full model (without inventions)	Patient care model
Independent variables			
Research group	0.27***	0.21**	0.14*
Beds	0.18	0.19	0.01
CMI	-0.58	-0.62*	-0.72**
Grants	-0.09	-0.09	-0.01
Urban	-0.14*	-0.12	-0.10
Constant	1.71****	1.74****	1.86****
R <sup>2</sup>	0.39	0.35	0.21

Note. The coefficient for beds is multiplied by 1,000. CMI = case mix index.

\* $p < .1$ ; \*\* $p < .05$ ; \*\*\* $p < .01$ ; \*\*\*\* $p < .001$ .

second hypothesis. The significance level of the coefficient for group membership was, again, lower for the patient care model than it was for the other two models ( $p < 0.1$ ), whereas the impact of the control variable CMI increased. The drop in impact was also documented by the lower  $R^2$  of .21 compared with .35 and .39 in the other two models. However, it seems that emphasis on research had a positive effect in all three models. Among the control variables, only urban location had a significant negative impact in the first model, whereas CMI had a significant negative impact on performance in the second and third models.

## Discussion

According to our literature review, this is the first study to measure the performance of, and to examine the existence of, strategic groups among AMCs. We developed a framework that allowed the performance of AMCs to be measured and have demonstrated that strategic group theory is a useful concept for identifying patterns of strategic choice among AMCs. Our study adds to earlier approaches to strategic group research by building upon findings drawn from research on strategic groups among hospitals and higher education institutions. In our methodology, we considered a broad range of inputs and outputs that had been found to be relevant for performance in other studies. The DEA framework allowed us to define one comprehensive single measure of performance that considered the multiple aims of AMCs. By using a superefficiency approach that allowed for efficiency scores beyond 1, we improved on the approach used to measure efficiency in other studies. To define strategic groups, we incorporated recent advances in cluster analysis and tested the impact on performance by using an OLS approach that controlled for structure-related variables.

Our results revealed significant differences between groups of AMCs in terms of their focus on research. By controlling for a number of other variables, we were able to demonstrate that group membership affects overall performance. The results remained stable even after the model had been altered, although the model that did not include inventions as an output variable showed a slightly less significant association. Thus, we are able to confirm our first hypothesis that membership in a strategic group that specializes in research rather than teaching is associated with higher overall performance. As concluded in previous studies (Nath & Sudharshan, 1997), identifying criteria that are assumed to represent mobility barriers is the crucial point in strategic group research. Therefore, our findings suggest that research activity represents an important strategic variable and a mobility barrier for AMCs.

The impact of strategic group membership on performance in the delivery of patient care was lower than the impact on overall performance. However, we can still confirm our second hypothesis that membership in a strategic group that specializes in research rather than teaching leads to higher performance in the delivery of patient care. It seems plausible that staff members in research-orientated AMCs have cutting-edge knowledge that can facilitate care processes, especially in highly complex cases. However, the finding that a research specialization among AMCs leads to higher performance has not been found elsewhere. An important question arising from this is whether these results can be generalized beyond AMCs—that is, whether other hospitals can also increase their performance by initiating research programs. To address this question, future studies might seek to replicate this approach when investigating hospitals that are more loosely affiliated with higher academic institutions.

Clearly, the impact of structure-related variables is minimal, which confirms the relevance of strategic variables as opposed to structure-related variables. Urban location turned out to be significant in the first model, thus confirming our assumption that urban location would have a negative impact on performance. Because the significance of the impact of CMI increased in the patient care model, it can be assumed that differences in case mix can explain at least some differences in performance among AMCs. As expected, a higher CMI lowers the performance of AMCs.

Our study results are consistent with other studies that have found evidence supporting the existence of strategic groups among hospitals (Ketchen, Thomas & Snow, 1993; Madorran García & de Val Pardo, 2004; Marlin, Lamont, & Hoffmann, 1994; Short, Palmer, & Ketchen, 2002). However, our findings contrast with those of Warning (2004), who was not able to identify any strategic groups among universities (i.e., as opposed to university hospitals) with regard to research versus teaching. This might be explained by the complex interaction between patient care, teaching, and research in AMCs, which is different from the interaction between teaching and research in universities that do not have medical departments. Future research is needed to examine this complex interaction in AMCs in greater detail.

When interpreting our results, it is important to keep in mind that our study has several limitations. The small sample size is clearly one of these. Although small samples are common in studies on strategic groups (Bogner et al., 1996; Leask & Parker, 2007), our findings would have been more robust had our sample size been larger. A common critique of the DEA methodology is that efficiency scores vary depending on the inputs and outputs included (Jacobs et al., 2006). We addressed this concern by including different model variations that confirmed the robustness of our results. However, there might have been other relevant outputs, such as the number of emergency admissions, which we were not able to include and which may have led to other results.

Concerning the definition of strategic groups, there might have been other potential dimensions characterizing strategic behavior such as networking with general hospitals and specialties offered. The use of variables representing these dimensions was mainly limited by the availability of data. Further research should include more variables on possible strategic dimensions as well as on the structure and the regulatory environment of AMCs, which may also explain performance differences.

Finally, it might have been appropriate to include variables for quality of care, such as adjusted readmission rates, which could affect the model performance scores. However, the use of quality variables was constrained by

the availability of suitable data. Moreover, we do not feel that this has subjected our study results to bias as teaching status has been found to be related to quality (Ayanian et al., 1998; Keeler et al., 1992; Taylor et al., 1999).

## Practice Implications

Managers and scholars share the quest to explain performance of AMCs. This study provides important insights into the interplay of strategic choice, structural determinants, and performance of AMCs. First, our findings suggest that strategic choice of AMCs does in fact matter for performance, whereas structural determinants are of minor importance. This provides an important justification for managers to develop suitable strategic concepts for AMCs and provides a rebuttal to those who maintain that the performance of AMCs is mainly driven by external influences. Second, our study suggests that membership in a strategic group focusing on research may increase performance. Thus, if low organizational efficiency is detected, managers need to consider analyzing whether their AMC belongs to an appropriate strategic group. A clear emphasis on research may not only increase overall efficiency, but also increase efficiency of patient care. Finally, as research obviously represents a mobility barrier, a change in strategic direction will only take effect over the long term.

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## **CHAPTER 3: The impact of resource input on research performance of surgeons in academic medical centers**

Von Reitzenstein C, Schreyoegg J, Schultz C (2010). The impact of resource input on research performance of surgeons in academic medical centers. IEEE Transactions on Engineering Management (under review)



## **MANAGERIAL RELEVANCE STATEMENT**

A significant part of medical technology research and development has its origin in hospitals. However, in the analysis of medical research, i.e. medical devices or pharmaceuticals, most attention has been so far dedicated to the later stages of the new product development process, i.e. focusing on patents as indicators of inventions or the internal product development process in firms. In order to develop a comprehensive understanding of the R&D process, we suggest that earlier stages of the production cycle should be considered also. Therefore we aim to shed light on the determinants of research activities by physicians in academic medical centers. Specifically, we aim to determine the impact of resource input on research performance of surgeons in academic medical centers. Basing on empirical analysis, we formulate recommendations for hospital managers, how they can effectively maximize research performance of physicians. Our results have implications beyond the health care context, as they show that different kind of resources have different and in some cases nonlinear effects on individual R&D performance.

## **ABSTRACT**

Although major parts of medical and medical technology research is physician-driven, very little attention has been paid to the antecedents and underlying mechanisms of hospital-based research. Therefore, building on the findings of the resource-based view and organization psychology, this paper analyses the impact of three different resource types, specifically, individual, academic medical center (AMC), and network resources on surgeons' research performance. We suggest that resource input of all three resource types follows the law of diminishing marginal returns. Results, based on a sample of 255 surgeons in 18 AMCs in the United States, partially support our hypothesis, indicating that individual resources impact research performance positively, while access to AMC-resources follows an inverted U-shaped relationship, showing diminishing marginal returns. The relationship between network resources and research performance is U-shaped, so that research performance is minimized for moderate intensity of external network access. In order to maximize research performance of surgeons, AMC-managers should make sure

that surgeons have profound technological knowledge and should invest in ongoing education. Further, AMC-managers should emphasize that AMC-resource endowment is adequate but they should be cautious when calls for additional resources arise. Finally, managers should be aware that only intense external network activity is valuable.

**Index terms** – Academic medical centers, resource based view, research performance

## **INTRODUCTION**

A steady stream of novel products, services, or processes is widely assumed to be a vital source of superior organizational performance and long-term survival (e.g. Jansen et al. 2006). While this could be said for all industries, it is particularly true in fast growing and research intensive industries, like the health care sector, which is confronted by a staggering array of complex challenges, including ongoing pressures for new diagnostic and treatment technologies, and the emergence of new organizational forms (Short et al. 2002). Therefore, much research has been devoted to the evaluation and management of medical research and to the settings in which it may be found in this sector (Kumar and Motwani 1999). Nevertheless, only little attention has been paid to the antecedents of research activity in hospitals. This is remarkable, since major portions of health care advancements are either piloted or applied in hospitals, or even invented by physicians or other researchers in hospitals.

In contrast to other industries, research activities of hospitals are not dedicated to special R&D departments and can be instead seen as a bottom up process where medical research is conducted at the level of individuals. Thus, hospital research performance depends to a large extent on the innovative capabilities and engagement of their employees. In spite of the relevance of research activities of hospital employees, only a few studies analyze the drivers of research conducted by physicians in hospitals (e.g. Lettl et al. 2008; Lüthje 2003). Hence, the aim of this paper is to close this research gap and to determine some antecedents and underlying mechanisms of individual research performance in hospitals.

Due to the central role that resources play as critical drivers of individual research performance (e.g. Lettl et al. 2008), we focus on the impact exerted on individual research performance by different resource types. The conceptual framework of our analysis is based on the theory of the resource-based view (RBV), which has emerged as a very popular theoretical perspective for explaining performance and has been already applied in hospital settings (e.g. Short et al. 2002). Scholars historically have used “resources” as a general term to refer to inputs into organizational processes (Barney 1991). The RBV is originally a theory of the firm but recent theoretical and empirical research shows that antecedents to competitive advantage and firm performance can be found not only on the firm level but also on individual and network levels (Eisenhardt and Martin 2000; Rothaermel and Hess 2007). Consequently, the RBV has lately also served as a theoretical foundation for the analysis of individual performance (e.g. van Rijnsoever et al. 2008). We complement the individual approach to the RBV by considering individual level influences following the rich body of organization psychology literature that explains how individuals, e.g. employees, cope with specific situations based on their desire to perform innovative activities and resource availability (Pearlin and Schooler 1978).

We follow the idea that relevant resources can be found on an individual level (e.g. competences and experience), may be provided by the hospital (e.g. time, funding or top management support) and can be accessed through external networks resources (e.g. research contacts). Our aim is to determine how these various resource types impact the research performance of surgeons. We further hypothesize that resources are important for research performance but that resource access will not be valuable in every situation. In other words, we assume that a point will be reached beyond which an increase in resource input will not yield performance improvement.

We will test our hypotheses using a dataset of 255 surgeons at 18 US academic medical centers (AMCs), some of which have the strongest research performance in the United States. Research performance was measured by ISI Web of science listed publication citations while resource access was drawn from a survey. To increase the validity of our results, rigorous econometrical techniques, such as factor analysis and negative binomial regression, were applied.

**THEORETICAL FRAMEWORK AND HYPOTHESES DEVELOPMENT**

The resource-based view (RBV) of the firm, based on the work of Wernerfelt (1984) and Barney (1991), has become one of the most frequently used theoretical foundations for explaining sustainable competitive advantage. As the RBV evolved, greater emphasis was placed on the properties of resources, and, in particular, differences between more tangible input resources (people, machinery, financial capital) and the intangible knowledge-based resources began to be distinguished (Kogut and Zander 1992; Teece et al. 1997). Recent theoretical developments emphasized that the diverse forms of resources can either be found at the individual, firm, and/or network level (Eisenhardt and Martin 2000). Overall, the RBV and its successive theoretical advancements identified resources as critical drivers of organizational performance and suggested that more resources would lead to higher research performance. The RBV theory is, however, more a theory of the firm than an individual approach, despite the fact that it has been recently also applied in university settings (e.g. Xu et al. 2010) and to individuals (e.g. van Rijnsoever et al. 2008). This makes sense in particular for the case of universities and AMCs, since their scientific performance is an aggregate function of the research output of its medical personnel.

Recent research reveals the importance of differentiating various resource types. Galbreath (2005) finds resources that are intangible in nature (e.g., know-how and capabilities) have a more significant impact on the firm success than tangible resources. Rothaermel and Hess (2007) empirically confirm theoretical contributions by Eisenhardt and Martin (2000) that a firm's research performance is driven by individual, firm, and network effects. We propose that this is also the case for an individual's research performance and suggest that the individual capabilities of surgeons, the resources and support the hospital provides them with, and, lastly, the surgeons' network ties, contribute positively to their research performance.

Organization psychology literature also emphasizes the relevance of individual contributions for research performance and the potential role of the availability of resources. Pearlin and Schooler (1978) accentuate the role of resources as enabling and stimulating mechanisms for creative actions and promoting search for ideas. Scott and Bruce (1994) also describe individual attributes,

organizational support, and the access of additional resources through team work as critical antecedents of innovative behavior. Creativity of employees is driven by tangible resources provided by the organization, like financial endowments, facilities, or simply time, but this creativity is further related to intangible organizational and supervisory encouragement as well as the support by the work group (Amabile et al. 1996). Shalley and Gilson (2004) summarize the existing literature on creativity in a similar manner and state that social and contextual factors on different levels influence individual innovative outcomes. While this seminal research focuses on the role of firm internal resources, more recently several authors highlight the role of external resources for individual innovation behavior, like support by professionals outside their organization and also outside their functional domain (Hulsheger et al. 2009).

Based on these findings, one could argue that an individual's research performance is a positive function of individual, firm (AMC), and network resources. However, the assumption that output will continuously increase with more resource inputs is questionable. Already beginning with classical microeconomic theory and in particular the theory of diminishing marginal returns, the literature states that an increase in inputs in a given production process will lead to a decrease of additional outputs (Samuelson and Nordhaus 2001). Simply put, the theory suggests that after some point, successive equal increments in the quantity of a good yield progressively smaller increases or even decreases in returns. This proposition of nonlinear relationships between inputs and output might hold true for resources employed in the research efforts of a firm. Reasons and theoretical underpinnings for decreasing slopes are manifold. As more resources are provided, the amount and variety of different activities and thereby the complexity of the research and development (R&D) portfolio are likely to increase. Complexity itself causes more intensive information processing and project coordination activities (Pich et al. 2002) – at the cost of research capacity. Additionally, transaction cost economics (Williamson 1975) reflects the increasing costs that accompany extra resources because it becomes increasingly difficult to find promising topics and to control R&D processes. Finally, agency theory states that the usage of organizational resources by individual researchers cannot be completely observed, which might cause inefficient use of additional resources (Jensen and Meckling 1976).

Moreover there is multifaceted empirical evidence that supports the notion of diminishing marginal returns for additional resource input in all three resource dimensions – individual, AMC, and network resources. Human capital and tacit knowledge have been identified as individual resources and important antecedents of research performance. They account for an individual's ability to transform the given resources into new products. Literature on the relation of investment in human capital and research performance suggests that education productivity will not always yield higher levels of competence (Schultz 1961). With these observations in mind, we put forward our first hypothesis as follows.

*H1: The relationship between individual resources and individual research performance has positive but nonlinear characteristics.*

While many studies find positive conjunctions between tangible resource input and performance (e.g. Parthasarthy and Hammond 2002), there is also literature that suggests non-existing, very weak, or nonlinear relations. Slack resources have been shown to have only a weak impact on organizational innovation (Damanpour 1991). Also, individual innovative behavior is only weakly influenced by tangible resources (Amabile et al. 1996) or not at all (Scott and Bruce 1994), which leads to our second hypothesis:

*H2: The relationship between AMC resources and individual research performance has positive but nonlinear characteristics.*

Lastly, the impact of size and strength of external networks on knowledge creation can show diminishing marginal returns, such as shown for the case of biomedical scientists (Mc Fadyen and Canella 2004), in particular if the network consists of weak and diverse relationships (Baer 2010). It is very likely that these observations hold true for academic surgeons as well. Therefore, we suggest that increasing access to networks will not necessarily yield higher research performance, resulting in the third hypothesis of this study:

*H3: The relationship between network resources and individual research performance has positive but nonlinear characteristics.*

## **METHODS**

### **Setting and Data**

We test our hypotheses merging survey data with objective data on the research performance of surgeons in academic medical centers. Information about the resource access is generated using a questionnaire, based on the prior validated scale where possible. During the preparatory phase of the study, a preliminary version of the questionnaire was distributed to 25 surgeons of various subspecialties, who subsequently provided us with feedback, which was used to refine the final survey instrument. We then contacted 70 US medical schools with the strongest research performance as ranked according to the Higher Education Evaluation and Accreditation Council of Taiwan (HEEACT 2009). 18 medical schools agreed to participate in the survey, five of which were ranked among the top 20 medical schools in the US (HEEACT 2009). In these 18 medical schools we distributed our questionnaire to 550 surgeons. 293 surveys were completed, which corresponds to a response rate of 53%. Of these responses, six had to be excluded due to missing data, resulting in a total of 287 useable questionnaires. Subsequently, data from the survey were combined with objective data on participating surgeons' R&D performance, which we measured by counting refereed journal citations that were attributable to each surgeon and had been indexed on the ISI Web of Science. Because 32 surgeons had not included their names on the questionnaire, data on a total of 255 surgeons were ultimately included in our analysis.

Of these surgeons, 214 were men and 41 were women. The mean age of the sample was 48.1 years. The subspecialties of the involved surgeons are general surgery (SURG; N=112; including transplant surgery and surgical oncology), orthopedic surgery (ORTHO; N=58; including trauma surgery), cardiothoracic surgery (CARDIAC; N=31); 54 surgeons belong to the miscellaneous subspecialties group (OTHER; including neurological, plastic, pediatric, ophthalmological, urological, head and neck, gynecological, and otolaryngological surgery).

### **Dependent Variables**

Although indicators such as technology licenses (Chang et al. 2009; Nelson 2009; Powers and McDougall 2005; Thursby and Thursby 2002), patents and patent citations (He et al. 2009; Trajtenberg 1990), publications and publication citations (He et al. 2009), or a combination of these (Wallmark et al. 1988) have been considered as variables explaining research performance, publication citations have remained the indicators of choice in a university setting. Therefore, individual research performance is indicated by the number of citations of an individual surgeon's publications. These represent an essential part of virtually any academic career in medicine and the natural sciences (Dundar and Lewis 1998; Olson 1994). While publication counts are a valid proxy for research activity, citations are increasingly viewed not only as a measure of activity but also research quality (He et al. 2009). Due to the lack of standardized authorship conventions that would have allowed us to estimate the extent of a surgeon's contribution to each paper, we decided to use the total citation count regardless of the position at which the surgeon's name appeared in each author list of a paper. Citation records were obtained from the ISI Web of Science, which covers more than 10,000 journals from over 100 scientific disciplines. Because the errors inherent in electronic databases necessitate stringent quality control procedures (Hood and Wilson 2003), we identified participating surgeons by matching their departments and institutions in addition to their names. To reduce age biases and to increase robustness, we selected a 6-year period (2005 through 2010), counting all articles in which the participating surgeons appeared as authors.

### **Independent Variables**

To comply with the theoretical constructs derived in Section 2 we included questions on individual, firm, and external resources in our survey using five-point Likert scales with items ranging from (1) "strongly disagree" to (5) "strongly agree". Three distinct factors were identified through exploratory factor analysis that fit the criteria of each resource type which we entitled *individual resources* ( $\alpha=0.78$ ), *AMC-resources* ( $\alpha=0.87$ ), and *network resources* ( $\alpha=0.79$ ). All factors have



significant Cronbach's alpha with values  $> 0.7$ . All items and their factor loadings are listed in Table 1.

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Please insert Table 1 about here

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### **Controls**

To reduce the likelihood of unobserved heterogeneity among surgeons, we controlled for several attributes. First, we controlled for differences between male and female surgeons (GENDER), which is especially important in a male-dominated discipline like surgery. Second, because academic physicians must care for patients in addition to fulfilling their research duties, we also controlled for the percentage of their working time spent on research, which is conceptualized in the "time" variable (survey question: "Please indicate the percentage of your working time that you devote to research activities"). Third, we controlled for age to reduce career-stage biases. Lastly, we controlled for differences between the surgeons' subspecialties, specifically the groups *surg*, *ortho*, *cardiac*, and *other* as defined in the previous section.

### **Analytical Technique**

The dependent variables of this study, citations, is a nonnegative, integer count variable. When choosing an appropriate econometric model to examine how research performance of surgeons is influenced by resources, we had to consider that the distribution of our dependent variable was largely skewed to the right and contained a substantial proportion of zeros (22%). Several estimation techniques have been proposed in the literature to deal with distributional characteristics like these. Among them are Poisson and negative binomial (NB) models, as well as zero-inflated Poisson (ZIP) and zero-inflated negative binomial (ZINB) models (Yau et al. 2003). To determine the best model fit among ZINB, ZIP, NB, and Poisson, we followed the steps proposed by Greene (1994) and Chou and Steenhard (2009).

Verified by a statistical test for overdispersion (Gourieroux 1984), the negative binomial estimation provides a significantly better fit for the data than the more restrictive Poisson model. To find the

better fit between NB and ZINB we applied the Vuong-Test (Vuong 1989), which compares the conditional model with the true conditional distribution, to determine whether the NB model should be rejected in favor of the ZINB model. The test suggested that the NB models were as efficient as the ZINB models. Other common criteria for fit such as AIC (Akaike's information criterion) and BIC (Bayesian information criterion) indicated that the NB model had the better fit. Thus, we used the NB specification throughout our models. In theory, either fixed- or random-effects specifications can be used to control for unobserved heterogeneity (Greene 2003). We applied a Hausman specification test (Hausman 1978), and its results revealed that the random-effects estimation is more appropriate. Therefore, we applied the following random-effects negative binomial model,

$$y_{ij} = \beta_{0j} + \beta_1 x_{ij} + \varepsilon_{ij}$$

$$\beta_{0j} = \beta_0 + u_j$$

where  $y_{ij}$  is a nonnegative integer count variable, representing the  $i$ th surgeon's research performance. The intercept for the  $j$ th AMC is given here as a fixed component  $\beta_0$  and a random component  $u_j$ , which indicates the random effects among AMCs on the dependent variable, while  $x_{ij}$  is a vector of explanatory variables. The random term  $\varepsilon_{ij}$  represents the unexplained variation for surgeons within an AMC. The random terms  $u_j$  and  $\varepsilon_{ij}$  are assumed to be normally distributed with zero mean.

## FINDINGS

Table 2 depicts the descriptive statistics and bivariate correlation matrix, while Table III presents the regression results. We first estimated the baseline model with individual, AMC and network resources as well as control variables only (Model 1). The subsequent Model 2 included squared terms for all resource variables to explore whether resource input has nonlinear characteristics or diminishing marginal returns, as proposed in hypotheses 1-3. We performed Wald tests for the null hypothesis that the parameters of the model with squared effects do not differ compared to the

model without squared effects (i.e., the parameters of the squared variables are assumed to be zero). The chi-square statistic indicated strong significance ( $p < 0.001$ ) for the model with squared effects (Model 2) compared to the baseline model including no squared effects (Model 1). Therefore, the model with squared effects differs significantly from the model without squared effects.

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Fig. 1 presents the predicted effects of individual, AMC, and network resources on the individual research performance and their data distribution under the assumption that all other variables in the regression equation are held constant.

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We proposed that the relationship of resource input and individual research performance is characterized by diminishing marginal returns. However, as can be seen in our models, we were not able to find support for all resource types. To begin with, our data did not provide significant support for the assertion that individual resources have diminishing marginal returns (hypothesis 1). This relationship is linear ( $p < .05$ ) with a non-significant squared effect of individual resources on citations. This finding is in line with recent empirical studies (e.g. Lüthje 2003) according to which the in-depth knowledge of surgeons about product architecture, materials used, and technologies incorporated was proved to have significant influence on innovation activity. Thus, the better surgeons are educated in terms of their technological knowledge and understanding and the more interest they have in technological advancements the better they perform in their research efforts. Importantly, there are no diminishing marginal effects in this regards.

In line with hypothesis 2, AMC resources have a strong U-shaped relationship with individual research performance. An increase in access to AMC resources, in fact, results in a decrease of

individual research performance after a certain tipping point is reached ( $p < 0.001$ ). This finding is also in line with previous research. Although tangible resources were identified as an important determinant of innovativeness (e.g. Crook et al. 2008), it has been shown on a firm level that there is a nonlinear (inverted U-shape) relationship between resources and research performance (Stock et al. 2001). A potential explanation for the shape of this curve could be that surgeons put a lot of emphasis on their research performance in order to obtain third party funding (AMC resources), as long as their resource endowment is low. Once they are known in the community, these surgeons will receive research grants more easily but have less motivation to transform the rewarded resources into research output. As a result, we can state that surgeons might not always be able or willing to transform additional resources into research output, after a certain resource level has been reached.

Contrary to hypothesis 3, network resources do not show diminishing marginal returns. Their relationship with research performance has classic quadratic U-shape characteristics, where moderate levels of network intensity lead to the lowest research performance. Although network activity at first negatively impacts research performance, there is a bottom point after which the slope becomes positive and where more network activity has positive performance implications. Recently, several studies analyzed the importance of inter-university and industry collaborations (e.g. He et al. 2009). All studies found a positive relationship between activities in external networks and research performance. For higher levels of networking intensity our results confirmed these findings from an individual perspective and showed a significant positive relationship. As the U-shaped slope shows, network activity only pays off when it is deep enough, thus surgeons only benefit from being in contact with colleagues from outside their hospitals when network ties are deep and well established. However, this result disagrees with prior findings of McFadyen and Cannella (2004), which show that the size of external networks of biomedical scientist has an inverted U-shaped relationship with the number of publications in journals with a high impact factor. This controversy may be related to conceptual differences between our study and the McFadyen and Cannella study. First, we did not account for the impact factor of the journal but for the effective number of citations a research has generated. We believe that the journal impact factor

is only indirectly related to the quality of a paper. Second, we did not focus on the number of co-authors but rather on the access to external knowledge and support. Baer (2010) revealed a similar quadratic relationship between network size and creativity for the case when the strength of network ties is high and the diversity of the partners is low. While we do not have detailed information about the nature of the external relationships, it might not be farfetched to argue that external knowledge and support can only be provided if strong ties exist.

Our study has several strengths as well as some limitations. It is among the first that analyze the underlying mechanisms of medical research in hospitals with the focus on resource input and its performance implication. Thereby, the present study distinguishes between several resource types. Another strength of this paper is the quality of the data. We were able to gather data from some of the best medical universities and hospitals in the United States. The surgeons were well distributed over the various subspecialties, represented a broad age range (32–73 years), and included both the individuals who were very active in research and those who were not. Although the sample size was relatively low with respect to RBV studies of the firm, it was comparable to or even larger than the studies that analyzed research performance of individuals (Galbreath 2005; He et al. 2009; van Rijnsoever et al. 2008). Additionally, as we used objective information for our dependent variable, we were able to avoid problems related to a common source bias.

Lastly, we checked the robustness of our results in several ways. To begin with, we tested alternative count data specifications including Poisson and ZINB models. The modifications had very little impact on the coefficients while all effects remained significant. Second, to assess how sensitive our results are to the reported random-effects specification, we additionally applied the fixed effects estimation. The results remained robust. Third, we ran models with the number of publications as an alternative dependent variable. The main coefficients turned out to be identical throughout the model but slightly lost in significance.

On the other hand, this research has several limitations, which potentially open pathways for future research. Chief among these is our use of total citation counts as the sole measure of research performance. Analyzing journal articles and their citations is fraught with difficulties related to

authorship, journal quality, and publication type. Although our analysis does not differentiate between articles based upon the order of authorship, we initially considered the number of articles with first authorship as a dependent variable. This practice resulted, however, in a sample that was too small for statistical evaluation. Future studies on similar topics might benefit from including additional measures of research performance, such as, for instance, patent counts. Unfortunately, using patent counts was not a solution in our case, as the search in our sample using the PATSTAT (2009) database revealed that 225 patents had been filed by 34 surgeons, which also would have been too small for a meaningful study.

Some results, especially those on individual resources, might be attributable to our choice of measurement rather than the underlying effect of the mechanism. Future research could attempt to apply other measures for human skills and individual capabilities. Similarly, it has to be recognized that the resource variables were measured by self-rated Likert-type scales rather than through objective measurements. By using objective data sources, future research could increase the validity of the achieved results.

## **PRACTICE IMPLICATIONS**

In this paper, we set out to analyze the impact of resource input on the research performance of surgeons in AMCs. Building on the RBV and organization psychology literature we assumed that research performance is influenced by individual, AMC, and network resources. Moreover, we questioned whether this relation is linear positive and proposed that after a certain tipping point additional resource input will not necessarily yield additional performance. Our assumptions were only partially supported by our data.

We were able to show that the research performance of surgeons is indeed strongly dependent on the resources they had access to. In other words, research performance is dependent on a set of attributes, such as individual technological skills, tangible resources such as technological equipment, and, lastly, the opportunity to gather inspiration and ideas through external communities and cooperation. Nevertheless, we could also show that the actual impact and form of

relationship varies according to resource type. While surgical research constantly benefits from individual resources, our results also reveal that for the case of AMC resources certain kinds of saturation occur. Namely, when a particular resource level is reached, additional resources will reduce research performance. Moreover, network activity is only beneficial to research performance when it is intense and profound, whereas it hinders performance when activity is at a lower level. Consequently, the deployment of individual, AMC, and network resources has to be differentiated according to the resource type.

AMC managers should, therefore, make sure that their surgeons are technologically trained and experienced, are eager to adopt new and innovative techniques and technologies, and keep abreast of the latest technical trends. Further, managers should make sure that researchers have sufficient access to AMC resources, such as time, money, laboratory access, and nursing as well as technical and top-level support. Nevertheless, managers should react cautiously to calls for additional resources. If these calls arise, it is vital to analyze the relationship between resources endowment and resource performance present in the particular situation before additional resources are provided. Lastly, managers should make sure that external network activity is focused and intense. Sporadic outside of domain contacts and conference attendance will not lead to the generation of new ideas and will not give impetus for innovative projects.

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Table 1. Factor items and loadings

<b>Factor 1: Individual resources (<math>\alpha=0.76</math>)</b>	<b>Factor 1</b>	<b>Factor 2</b>	<b>Factor 3</b>
In terms of medical technologies, my requirements change earlier than those of most other colleagues.	0.69	0.07	0.06
I have experienced significant benefits from adopting very new innovative techniques and technologies.	0.77	0.09	0.05
I am regarded as an opinion leader in my field of expertise.	0.70	0.01	0.26
I always keep abreast of the latest technical trends and developments related to my work.	0.69	-0.01	0.19
I am often asked by other colleagues to solve technical problems.	0.62	0.00	0.33
<b>Factor 2: AMC resources (<math>\alpha=0.87</math>)</b>			
I have sufficient time to innovate.	0.05	0.68	0.22
The hospital provides me with sufficient funding to innovate.	-0.02	0.74	0.07
I have sufficient specialist staff supporting my activities.	0.08	0.74	0.10
I have sufficient administrative staff (e.g. study office) supporting my innovative activities.	-0.04	0.78	0.06
I have sufficient access to technological and laboratory equipment.	0.02	0.75	0.10
I receive sufficient top-level support.	0.05	0.81	-0.01
The organizational culture of my institution encourages innovative behavior.	0.11	0.79	-0.06
<b>Factor 3: Network resources (<math>\alpha=0.70</math>)</b>			
I frequently exchange ideas with my colleagues outside of my hospital.	0.29	0.01	0.71
If I want to innovate, I know the right people outside of my hospital who could support me.	0.16	0.19	0.71
I visit exhibitions that present new medical technologies.	0.15	0.01	0.68
I study medical reference books and medical journals outside of my subject area.	0.11	0.12	0.68

Table 2. Descriptive statistics and correlation matrix

Variable		Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10
<i>Individual research performance</i>															
1	Citations	67.53	137.75	0.00	1127.00	-									
<i>Resources</i>															
2	Individual resources	3.59	0.70	1.40	5.00	0.15	-								
3	AMC resources	2.65	0.93	1.00	5.00	0.10	0.11	-							
4	Network resources	3.62	0.74	1.25	5.00	0.16	0.47	0.21	-						
<i>Controls</i>															
5	Gender	0.84	0.37	0.00	1.00	0.06	0.18	-0.02	0.04	-					
6	Time	14.25	15.83	0.00	80.00	0.22	-0.04	0.35	0.22	-0.18	-				
7	Age	48.16	9.47	32.00	73.00	0.13	0.14	-0.11	0.03	0.14	-0.19	-			
8	Surg	0.44	0.50	0.00	1.00	-0.01	-0.09	0.08	-0.06	-0.07	0.01	0.02	-		
9	Cardiac	0.12	0.33	0.00	1.00	0.02	0.09	-0.10	0.04	0.06	0.03	0.02	-0.33	-	
10	Ortho	0.23	0.42	0.00	1.00	-0.02	0.03	-0.04	0.03	0.04	-0.13	0.00	-0.48	-0.20	-
11	Other	0.21	0.41	0.00	1.00	0.02	0.01	0.02	0.01	-0.01	0.10	-0.04	-0.46	-0.19	-0.28

$n = 255$ ; All correlations above  $|0.10|$  are significant at  $P < 0.05$

Table 3. Results of the random-effects negative binomial regression

Variable	Citations	
	Model 1	Model 2
Intercept	3.82***	3.29***
<i>Dependent variables</i>		
Individual resources	0.36***	0.26*
AMC resources	-0.09***	1.25***
Network resources	0.15***	-0.42***
Individual resources × individual resources	-	0.01
AMC resources × AMC resources	-	-0.24***
Network resources × network resources	-	0.08***
<i>Controls</i>		
Gender	0.57***	0.64***
Time	0.02***	0.02***
Age	0.03***	0.03***
Surg (Reference)	0.0	0.0
Cardiac	-0.02	-0.06*
Ortho	-0.21***	-0.17***
Other	0.19***	0.31**
<i>Fit statistics</i>		
Log likelihood	-13257	-12845
LR chi-square (DF)	5312 (11)	6131 (14)
Improvement (Wald test; Chi2 (3))		824***
Comparison		Model 1

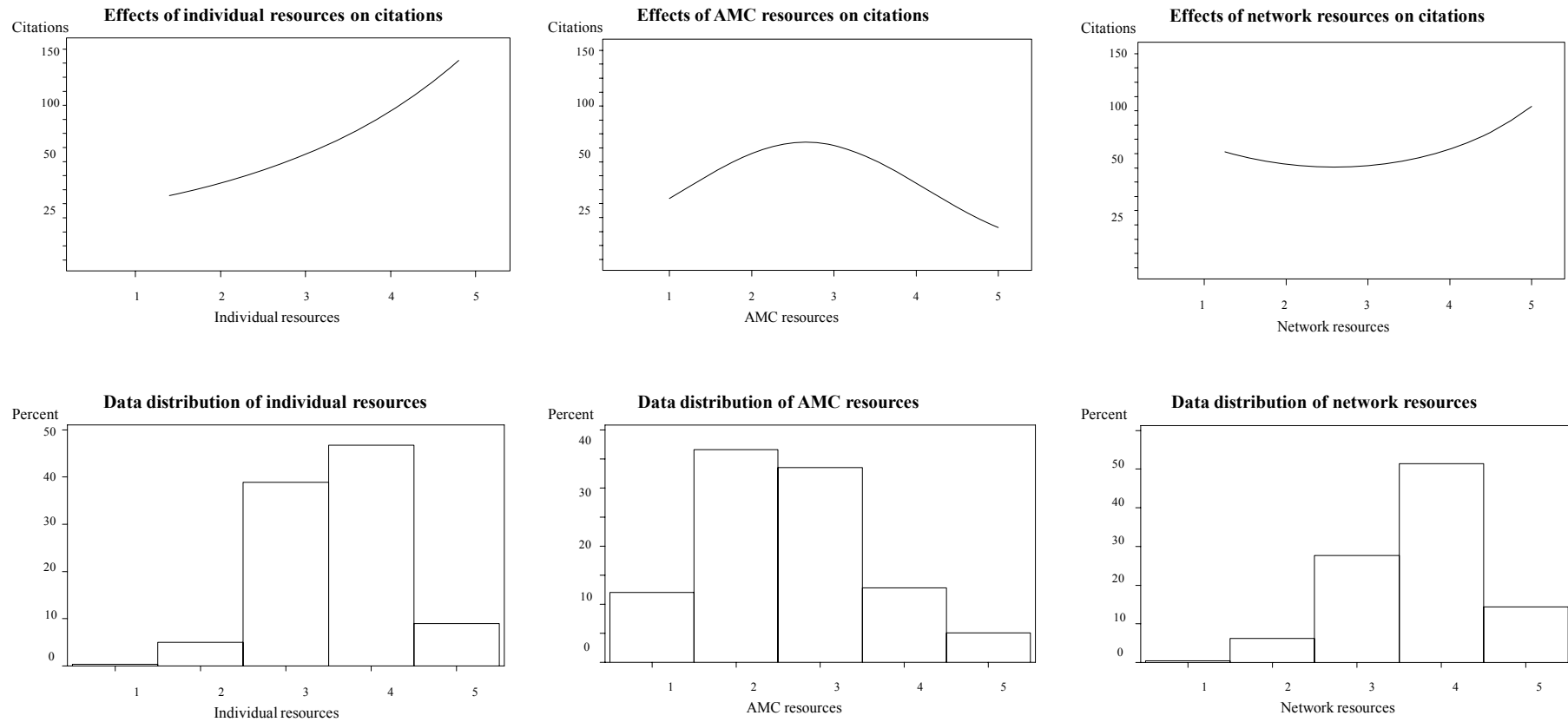
*n*=255 Note: Results are presented on the log scale because we used a log link function.

\*  $P < 0.05$

\*\*  $P < 0.01$

\*\*\*  $P < 0.001$

Figure 1. Effects and data distribution of individual, AMC and network resources on citations



## **CHAPTER 4: Team diversity and individual research productivity**

Von Reitzenstein C, Stargardt T, Schreyoegg J (2010). Team Diversity and Individual Research Productivity. Research Policy (under review).

## **ABSTRACT**

This article explores the impact of team diversity on individual research productivity. Using a theory of building diversity, we hypothesized that diversity as disparity negatively influences productivity, whereas diversity as variety stimulates productivity. Based on a sample of 5796 surgeons from 440 research teams in 50 US medical schools, we constructed several measures to model disparity and variety aspects of diversity such as diversity in hierarchical positions and gender (disparity) or diversity in educational background, star scientists, experience, and nationality (variety). Controlling for characteristics at the individual and the medical school levels, we applied multilevel negative binomial regression models and found that diversity in hierarchy (i.e. disparity) decreases research productivity, whereas diversity in education, additional qualifications, and membership of star scientist to a team (i.e. variety) stimulates research productivity. Diversity in experience, gender, and nationality had no significant influence on research productivity.

## **Keywords**

Team Diversity, Individual Research Productivity, Multilevel Modeling, Medical Schools

## **INTRODUCTION**

Academic research activity is increasingly viewed as an important contributor to the production of knowledge and thus to innovation and growth. A significant amount of work has been dedicated to quantify the impact of public research on economic activity (Salter and Martin 2001). Scholars have analyzed how firms use the knowledge produced by public research organizations (Cohen et al. 2002), which types of firms exhibit a greater tendency to draw on public research results (Mohnen and Hoareau 2002), and the channels used by both types of actors to interact (Cohen et al. 2002; Meyer-Krahmer and Schmoch 1998). Also, the potential benefits and drawbacks of



university–industry partnerships for universities have been examined (Poyago-Theotoky et al. 2002; Stephan 2001).

The internal organization of public research entities, however, is still far from having received enough attention despite some major theoretical (Dasgupta and David 1994) and empirical contributions (Stephan 1996). The lack of analysis concerning the organization of scientific activities itself and its effect on research productivity is even more surprising when compared to the huge efforts devoted to understanding the innovation process (Carayol and Matt 2006).

Nevertheless, numerous studies have examined the effect of individual attributes and factors on research productivity including age, gender, socioeconomic status, and educational background (Braxton and Bayer 1986; Hall et al. 2007; Levin and Stephan 1989; Stephan 1998; Tien and Blackburn 1996), along with several cultural and organizational dimensions (Conrad and Blackburn 1986). However, Stephan (1996) highlights that studies that only analyze the effect of individual factors without considering the team perspective or higher level influences have limited ability to explain research productivity because in many fields research is conducted in groups of individuals rather than by an individual alone. Thus, further investigation of academic research production should also take into account the collective level of organization, such as the research team or department or the university level (Carayol and Matt 2004, 2006; Dasgupta and David 1994). This is also in line with research on the antecedents of creativity and innovation in the workplace, in which team characteristics have been found to be important variables to explaining productivity (Hülsegher et al. 2009).

Moreover, organizations are increasingly adopting work group compositions that incorporate differences in functional or educational background, such as cross-functional and interdisciplinary project teams (van Knippenberg and Schippers 2007). Also, during the last two decades, organizations including universities have become more diverse in terms of demographic differences among people and, consequently, also groups in organizations have become increasingly diverse (Jackson et al. 2003; Williams and O'Reilly 1998). Research in the area of work team diversity has therefore also grown. Still, several comprehensive reviews have noted that

the findings do not provide a clear consensus regarding the performance effects of work team diversity (Harrison and Klein 2007; Jackson et al. 2003; Milliken and Martins 1996; van Knippenberg and Schippers 2007; Williams and O'Reilly 1998). In some studies, researchers have reported that team diversity is positively associated with team performance (Ely 2004; Van der Vegt et al. 2005). In other studies, team diversity has been found to negatively predict performance (Jehn et al. 1999; Leonard et al. 2004). A majority of these studies, however, have reported a non-significant relationship between team diversity and team performance. Furthermore, even within studies, the effects of gender, race, age, and tenure diversity on team performance have varied (e.g., Kirkman et al. 2004; Kochan et al. 2003). Recent research has therefore suggested that contextual factors at multiple levels of analysis influence and moderate the performance outcomes of diversity in teams (Bamberger 2008; Johns 2006; Rousseau and Fried 2001; Joshi and Roh 2009).

In this paper we analyze the effect of team diversity on individual productivity using the example of research productivity. Based on publication and citation records from 5796 surgeons who are members of 440 research teams in 50 US medical schools, we propose a multilevel framework with three levels, specifically, the individual, the team, and the medical school, to examine the impact of work group diversity on individual research productivity of scientists. Thereby we control for factors at the individual level as identified by previous research to have an effect on research productivity and carefully address contextual influences of team diversity at the medical school level as proposed by recent research on diversity (Joshi and Roh 2009).

The paper is structured as follows. In section 2, we define diversity and briefly discuss relevant theoretical foundations of team diversity. In section 3, hypotheses are developed accordingly. In section 4, we describe the research setting, the conceptualization of research productivity, and diversity measures as well as control variables at each level. Results are reported in section 5. Section 6 discusses potential implications of our results. Section 7 concludes with implications of our research for the management of research processes in the academic setting.

## **THEORETICAL BACKGROUND**

Diversity can be conceptualized as the distribution of differences among the members of a unit with respect to a common attribute, such as tenure, ethnicity, conscientiousness, task attitude, or pay. Harrison and Klein (2007) propose a categorization of diversity into three distinct types. Diversity may be represented by separation, variety, or disparity. Separation expresses differences in position or opinion reflecting disagreement or opposition, for example, concerning a particular attitude or value. Within-unit diversity may also be indicative of variety expressing differences in kind or category concerning information, knowledge, or experience among unit members. The third type proposed by Harrison and Klein (2007) is disparity reflected by differences in concentration of valued social assets or resources leading to vertical differences that may privilege a few over many.

Thus, diversity is a unit-level, compositional construct. In describing the diversity of a given attribute within a unit (e.g., a group or organization), one describes the unit as a whole, not a focal member's differences from other members, which is the subject of most relational demographic research (Tsui and O'Reilly 1989). Diversity, as we use the term, is attribute-specific. A unit is not diverse per se but is diverse with respect to one or more specific attributes of its members (Jackson et al. 2003). For our analysis, due to sample restrictions, we will focus on disparity and variety aspects of team diversity and their impact on individual research productivity.

Several theoretical perspectives have been used in the literature to guide diversity research. Often, these perspectives suggest contradictory effects and each perspective has received some, albeit mixed, support from empirical studies (Harrison and Klein 2007). Relations-oriented diversity attributes such as gender, race/ethnicity, and age, which are cognitively accessible, pervasive, and immutable, are mostly associated with social categorization processes (Fiske 1998; van Knippenberg et al. 2004). The social categorization perspective suggests that similarities and differences among work group members form the basis for categorizing self and others into groups, distinguishing between similar in-group members and dissimilar out-group members (van Knippenberg and Schippers 2007). People tend to favor in-group members over out-group

members and seem to be more willing to cooperate with them (Brewer 1979; Brewer and Brown 1998; Tajfel and Turner 1986). Thus, work groups might function more smoothly when they are homogeneous than when they are more diverse (van Knippenberg and Schippers 2007).

The social categorization perspective is amended by the similarity/attraction perspective (Williams and O'Reilly 1998) that focuses on interpersonal similarity (primarily in attitudes and values) as determinants of interpersonal attraction (Berscheid and Reis 1998; Byrne 1971). Both social categorization-based and similarity/attraction perspectives embody intergroup bias and negative attitudes toward dissimilar others in a group. Team diversity may therefore have a negative effect on performance. This is supported by findings of higher group cohesion (O'Reilly et al. 1989), lower turnover (Wagner et al. 1984), and higher performance (Murnighan and Conlon 1991) in more homogeneous groups.

In contrast to the social categorization and similarity/attraction perspective, the information/decision-making perspective that has evolved from ecologic and cognitive models of variation, selection, and retention (Campbell 1960) and the cybernetic principle of requisite variety (Ashby 1956) highlights the benefits of heterogeneity in information resources and suggests a positive impact of team diversity on performance. Thus, diversity attributes such as functional background, tenure, and range of network ties may enrich the supply of ideas, unique approaches, and knowledge available to a unit and stimulate unit creativity and performance (Williams and O'Reilly 1998). These aspects of diversity are assumed to contribute to a team's resource base and are associated with the exchange and integration of information and perspectives among group members (van Knippenberg and Schippers 2007). Diverse groups are likely to possess a broader range of task-relevant knowledge, skills, and abilities and members with different opinions and perspectives. Empirical findings from Bantel and Jackson (1989) support these findings and find team diversity to be associated with higher performance and level of innovation (Bantel and Jackson 1989).

Lastly, a third perspective is based on distributive justice theory (Cohen 1986; Deutsch 1985), tournament theory (Lazear 1995; Lazear and Rosen 1981), and status characteristics theories (Blau

1960; Berger et al. 1977; Oxoby 2002). According to these theories, relative comparisons among unit members of valued assets or resources that connote prestige or power lead to within-unit competition that may enhance performance. However, within-unit competition may also lead to a suppression of voice, reduced (quality of) communication, and interpersonal undermining (Harrison and Klein 2007); thus, team diversity may also have a negative impact on performance.

## **HYPOTHESIS DEVELOPMENT**

### **Disparity**

In the organizational literature, conceptual and empirical analyses of disparity are not very common compared to those of variety and separation. Disparity has been conceptualized as a socially valued or desired resource, such as pay, power, prestige, or status. Harrison and Klein (2007) propose that “(a) within units, members can differ in the extent to which they hold, or receive a share, amount, or proportion of this resource; (b) units differ in the extent to which the resource is distributed among or possessed by its members – in some units, members have equal shares of a resource, but in other units, one or a few members hold a disproportionate share relative to other unit members; and (c) differences among units in the extent to which their share is distributed equally among unit members lead to predictable and important consequences (e.g., fewer member expressions of voice).”

In the context of academic research, the above-described difference in access to resources is highly linked to career status. The higher the position of an individual, the better is the access to resources such as salary, information through networks, or third-party funding. In fact, career status has been shown to have an impact on research productivity (Porter and Umbach 2001). Evidence also indicates that attitudes toward teaching and research vary by career status (Baldwin and Blackburn 1981).

When disparity in a group is at its maximum, one member of the unit dominates all others; he or she holds the major share, if not all, of a valued unit resource (Harrison and Klein 2007). Related

to diversity-as-disparity in academic positions this would imply that there would be only one full professor with several assistant and associate professors. The full professor's power and resource access would far exceed that of others, creating high power and resource disparity in the team. According to the theories of distributive justice (Deutsch 1985) and tournament compensation (Lazear 1995; Lazear and Rosen 1981), we predict that high disparity in career status and thus in power and resource access increases competition among team members with low career status. As academic research heavily depends on the exchange of knowledge and experience and cooperation among group members, we believe that such competition will foster silence, suppression of creativity, and withdrawal (Hollander 1958; Pfeffer and Davis-Blake 1992; Pfeffer and Langton 1988) and will thus decrease productivity.

*Hypothesis 1: Diversity as disparity of team members in academic positions decreases individual research productivity*

Demographic diversity attributes such as gender can be conceptualized as separation, variety, or disparity. If gender differences reflect opposing beliefs, diversity can be conceptualized as separation; if men and women represent different sources of knowledge, gender diversity is defined as variety, whereas it stands for disparity when power differences between men and women occur (Harrison and Klein 2007). Tsui and O'Reilly (1989) found that subordinates who were dissimilar from their supervisors in terms of gender experienced higher levels of role conflict and role ambiguity than subordinates who were of the same sex as their boss. In terms of performance evaluations, supervisors reported greater positive affect for subordinates of the same gender and tended to rate their performance more highly (Tsui and O'Reilly 1989). Because current research calls for a contextual understanding of, in particular, demographic-related diversity (Joshi and Roh 2009), it seems appropriate to conceptualize gender diversity as disparity in the context of our study. The field of surgery is a very male-dominated medical and scientific discipline and it is likely that power concentrations occur in favor of one of the two genders. Thereby, performance disparity-related theories as described above predict negative effects of team diversity on performance. A highly unbalanced team in terms of gender might amplify the

effect by social categorization processes that disrupt group interaction via discrimination and self-segregation (Jehn et al. 1999).

*Hypothesis 2: Diversity as disparity of team members in gender decreases individual research productivity*

### **Variety**

Conceptualizing variety, Harrison and Klein (2007) suggest that “(a) within units, members differ from one another qualitatively – that is, on a categorical attribute, e.g., functional background, source of external information; (b) units differ in the extent to which their members are evenly spread across all the categories of the attribute; and, (c) differences between units in their relative spread or diversity in this characteristic will be associated, usually positively, with vital unit consequences, e.g., problem-solving or group decision quality and firm performance.” The authors further emphasize that the distribution of information, experience, or network resources available across unit members determine variety (Harrison and Klein 2007).

Diversity in the distribution of information among group members may be a result of a different knowledge base and perspective of team members (Jehn et al. 1999). These differences are likely to occur if team members differ in education and expertise. Diversity in education may enrich the supply of ideas, unique approaches, and knowledge available to a unit, enhancing unit creativity, quality of decision-making, and complex performance (Williams and O’Reilly 1998). However, it must be recognized that different educational levels may also promote conflict when individuals experience annoyance and anger when working with those of lesser or higher ability (Pelled 1996). Previous research has demonstrated that heterogeneity in educational background leads to an increase in task-related debates about content or processes in teams (Jehn et al. 1997). Being different from one’s colleagues in terms of education can also increase creative turnover (Cummings et al. 1993; Jackson et al. 1991).

*Hypothesis 3: Diversity as variety in education of team members increases individual research productivity*

Numerous empirical and qualitative studies provide convincing evidence that intellectual capital is not created equally, giving rise to the idea that significant heterogeneity exists within highly specialized human capital (Rothaermel and Hess 2007). Lotka (1926) was one of the first to note a highly skewed distribution pertaining to research output among scientists. When studying scientific publications in chemistry, he found that only about 5% of scientists were responsible for more than 50% of the total scientific research output. Past research in the field of academic productivity has indeed found that the research productivity of a department can be influenced considerably by the presence of a star scientist with specific research expertise (Dundar and Lewis 1998; Johnes 1988; Nederhof and van Raan 1993). Cole and Cole (1973) have reported, for example, that the most influential research being produced in many fields is being conducted only by a small number of all those engaged in research activity. Variety in terms of team members with specific expertise within units is therefore likely to increase productivity of other team members. Theoretical reasoning can be, again, drawn from the information processing perspective because variety in the percentage of team members being star scientists will increase resources.

*Hypothesis 4: Diversity as variety in percentage of team members being star scientists increases individual research productivity*

Arguments for experience are similar to those for education. Empirical findings about the effects of experience on performance to date are manifold, ranging from non-significant to positive and negative (van Knippenberg and Schippers 2007). However, experience cannot be as easily declared to be a variety measure. More experienced team members might be seen as possessing higher levels of task-relevant experience, tacit knowledge, or “street smarts.” Experience could thus be associated with power and be treated as a measure of disparity. In the special context of our study, however, we propose that experience is more of a variety measure representing a resource pool, in which younger scholars benefit from older ones and vice versa.

*Hypothesis 5: Diversity as variety in experience of group members increases individual research productivity*



In addition, several studies have analyzed the effects of diversity in nationality of team members. Most studies found negative effects on individual and group outcomes due to less job satisfaction (Verkuyten et al. 1993) or discrimination in the workplace (Bochner and Hesketh 1994), effects that can be assigned to social categorization processes. Belonging to a foreign nationality might also limit access to resources, similar to our arguments regarding gender. In this case, diversity in nationality would have to be classified as a disparity measure. However, other studies found that although short-term negative effects can be observed, in the long run groups may be able to obtain benefits from the greater variety of perspectives inherent within a diverse group (Millikan and Martins 1996; Watson et al. 1993). The United States has attracted the best scientists in the world and it has been proven in several studies that nonnative scientists often not only outperform their US colleagues but also stimulate performance of their peers (Corley and Shabarwal 2007; Lee and Bozeman 2005; Mamiseishvili and Rosser 2010; Stephan and Levin 2001). We therefore propose, with regard to the special context of this study, that diversity in nationality is conceptualized as a variety measure and that diversity in nationality is beneficial to individual productivity.

*Hypothesis 6: Diversity as variety in nationality of team members increases individual research productivity*

## **METHODS**

### **Setting and Data**

The Association of American Medical Colleges (2009) currently lists 131 medical schools that award MD degrees. Unlike other hospitals, academic medical centers (AMCs) are usually part of a university or medical school, and their mission is to combine patient care, education, and research, which can often lead to a trade-off among these three goals (von Schreyögg and Reitzenstein, 2008). Some medical schools do not conduct research and might not even have laboratories. We therefore chose the 50 most research-intensive medical schools listed in the Higher Education Evaluation and Accreditation Council of Taiwan (HEEACT 2009). Being listed can be regarded as a reliable indicator of current research activity at the cited universities (Aguillo et al. 2010).

Within the 50 medical schools, data were collected for surgeons in general, neurologic, orthopedic, pediatric, transplantation, cardiothoracic, vascular, trauma, and plastic surgery subspecialties. We decided to collect data on surgeons for three reasons. First, surgeons are the largest group of physicians at medical schools. Second, even though surgeons belong to many different medical subspecialties, the day-to-day business is homogeneous among them in that they all have to fulfill their duties in patient care, at the bedside, in teaching and research, and, in contrast to other physicians, in the operating room. Third, surgical research involves product-related as well as process-related research. This may allow results to be generalized to other areas.

From the medical schools' homepages we identified the names of all surgeons with assistant, associate, or full professor tenure. When resumes were available, we collected additional information such as alma mater or graduation year. Missing data were complemented with data obtained from web pages providing curricular information about physicians (e.g., [www.vitals.com](http://www.vitals.com) or [www.healthgrades.com](http://www.healthgrades.com)). Although curricular data can be a source of error due to deficiently provided data and exhaustion errors during the data collection process (Dietz et al. 2000), the overall reliability of such data has been widely acknowledged (Cañibano and Bozeman 2009; Gaughan and Bozemann 2002; Gaughan and Ponomariov 2008; Sandstrom 2009). Of 6178 names of surgeons initially identified, we had to exclude 357 surgeons due to missing data, leaving a final sample of 5796 surgeons (1192 general, 1482 orthopedic, 270 trauma, 630 cardiac, 848 neurologic, 334 pediatric, 401 plastic, 311 transplant, and 328 vascular surgeons). These surgeons were categorized into 440 research teams after a thorough review of departmental structures on the medical schools' homepages independently conducted by two researchers.

According to Cohen and Bailey (1997) based on a definition by Hackman (1987), a team is defined as a collection of individuals who are interdependent in their tasks, who share responsibility for outcomes, and who see themselves and who are seen by others as an intact social entity embedded in one or more larger social systems. Within this definition four types of teams can be identified in organizations today: (1) work teams, (2) parallel teams, (3) project teams, and (4) management teams. In contrast to parallel, project, and management teams, work teams are

defined as units responsible for the production of specific goods or services. Membership on a work team is typically stable, usually full-time, and well-defined (Cohen 1991).

For the purpose of our study we identified work teams (research teams) of surgeons. A potential team had to consist of three or more permanent team members, team members had to be working together on a common clinical subject as defined by the American Surgical Association, and team members had to have commonly conducted research reflected by project reports, publications, or other forms of dissemination. If proposed membership of a surgeon to a team differed between the two researchers, the case was discussed until a consensus was reached. Our “average” research team had 13.1 members, of whom about 4 were full professors, 3 were associate professors, and 6 were assistant professors; 87.1% of team members were men, 15.2% were foreign, and 13% had a PhD degree.

## **Measures**

### ***Measurement of individual research productivity***

The concept of research productivity embraces many different measures, from the number of presentations on scientific conferences and the number of journal publications and books to the numbers and amounts of grants received (Porter and Umbach 2001). Although journal publications are not homogeneous in (perceived) quality (e.g., peer-reviewed vs. non peer-reviewed journals), types of publication (e.g., original articles vs. comments), types of authorship, and number of coauthors, the number of publications in journals is clearly the most common measure of research productivity among universities and other research institutions (Dundar and Lewis 1998; Olson 1994). Although publication counts are a valid proxy for research activity, citations are increasingly viewed as a measure of research quality (He et al. 2009). We therefore rely on two measures as proxies for individual research productivity: a count of *publications* in peer-reviewed journal papers for a 5-year period (2004 through 2008) and a count of *citations* of these publications. To account for different publication and citation behavior among surgical

subspecialties we included variables representing surgical subspecialties in our regression. Subspecialties that did not differ in their publication and citation behavior were aggregated, for example, cardiothoracic and vascular subspecialties. The likelihood ratio test was used to test if the aggregation reduced model fit.

Publication and citation records of each surgeon were traced back in the ISI Web of Science, a database that covers more than 10,000 journals from more than 100 scientific disciplines. The authors were identified by matching name, department, and institution from curricular and Web of Science author data. In addition, a robustness check using other outcome measures such as the Hirsch-Index (Hirsch 2005) and average citations per publication was performed.

### ***Diversity measures***

We had three different data types in our dataset: continuous, categorical (more than two categories), and binomial variables (two categories). The literature has proposed multiple constructs to measure diversity for each data type (Harrison and Klein 2007; Tsui and Gutek 1999). To facilitate interpretation, we present all diversity measures that we have used and how they have to be interpreted in Table 1.

Diversity in continuous variables was modeled using standard deviation (SD). Thus a large SD corresponds to higher team diversity. Categorical data (more than two categories) was transformed into diversity measures using the Gini-Index (Gini). The higher the Gini the higher the concentration. When diversity is modeled as variety using the Gini, a high concentration (all team members of the same type) indicates small variety; when diversity is instead modeled as disparity, a high concentration (one team member holds the lion's share in a resource) indicates high disparity.

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Please insert Table 1 about here

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Binomial variables were modeled with the percentage of team members belonging to one category, for example, the percentage of female team members. The percentages were slightly modified to adequately model variety and disparity measures of diversity:

Diversity as variety: The more diverse a team is, the closer is the percentage to 0.5. For instance, if 5 team members in a team of 10 people have a PhD, the diversity in the team is at its maximum. To adequately reflect that diversity is at its minimum when 0 or 10 of 10 team members have PhDs, we subtracted 0.5 from the percentage measure and took two times the absolute value of the result. Consequently, the diversity as variety measure for binomial variables is between 0 (high diversity) and 1 (no diversity).

Diversity as disparity: When disparity in a group is at its maximum, one member of the unit outranks all others. So, if only one team member is female, diversity as disparity is at its maximum. Diversity as disparity decreases the more equal the ratio of genders become. Diversity as disparity is at its minimum when all team members are either male or female. We modified the approach described in (a), so that the maximum disparity (eg, only one team member is female) is at 1, while the minimum disparity is at 0.

Diversity in disparity is represented in the variables *Div-Hier* (Hypothesis 1) and *Div-Sex* (Hypothesis 2). The former, *Div-Hier*, is a concentration measure, calculated using the Gini, that represents the distribution of academic positions (assistant/associate/full professor) among team faculty. To ensure consistency in the data collection we excluded all other positions such as post docs or instructors. *Div-Sex* represents gender diversity, calculated as explained above for binomial variables representing diversity as disparity.

Diversity as a variety measure is represented in a number of variables. To model variety in education (Hypothesis 3), we calculated the variety of alma maters in a team (*Div-Edu*) using the Gini coefficient. Thereby we have considered all possible alma maters of those surgeons who graduated in the United States. Diversity was at its maximum. Another education measure is *Div-Score* in which we expressed the variety in the educational level of all surgeons in the team using the SD. The educational level of each surgeon was determined using the research ranking score

that the surgeons' MD-awarding alma mater had achieved in the HEEACT ranking (HEEACT 2009). Lastly, we constructed measures that expressed variety in the academic degrees calculated as explained above for binomial variety variables: *Div-PhD* represented variety in PhD degrees and *Div-MA* the variety in team members with an MPH or MBA degree serving as a proxy for new educational perspectives.

Diversity in star scientist (Hypothesis 4) was conceptualized in the *DIV-Star* variable calculated as explained above for binomial variables that measure variety. Based on the distribution of publication and citations, we identified researchers who were both publication and citation stars. Scientists were assumed to be stars if they published more than three times the SDs above the publication mean and if their articles were cited more than three times the SDs above the citation mean (Rothaermel and Hess 2007). Fifty-five scientists (0.9% of the sample) fulfilled our criteria.

Diversity in experience (Hypothesis 5) was obtained from variety in years that surgeons in a team had spent in practice after they had completed their MD (*Div-YIP*), using SD. Lastly, we calculated diversity in nationality (*Div-Nat*) (Hypothesis 6). Surgeons were considered as foreigners if their medical degree was awarded by a university located outside the United States. The variable was calculated as explained above for binomial variables that measure variety.

### ***Control Variables***

Previous research has identified several attributes at the individual level that potentially influence individual research productivity, such as age, gender, socioeconomic status, and educational background (Braxton and Bayer 1986; Hall et al. 2007; Levin and Stephan 1991; Stephan 1998; Tien and Blackburn 1996), along with several cultural and organizational dimensions (Conrad and Blackburn 1986). Specifically, we controlled for years in practice (*YIP*), academic position (*Assistant/Associate/Full*), gender (*Sex*), education abroad (*Foreign*), educational level (*Score*), and PhD and MA degrees (*PhD, MA*).

On the medical school level, we controlled for the number of full-time faculty members (*Size*), the student per faculty member ratio as a proxy for teaching load (*Teaching*), productivity defined as

inpatient cases per faculty member (*Productivity*), and the amount of grants per faculty member (*Grants*) to control for the intensity of third-party funding.

### Empirical Strategy

We hypothesize that research output of surgeons is a function of individual surgeon characteristics, team level diversity measures, and contextual factors on the medical school level. It is important to recognize that individual characteristics and attitudes can differ for each surgeon, but team diversity measures are the same for all surgeons working in a given research team and contextual factors are the same for all research teams in a given medical school. As a result, observations across surgeons are not independent. This “intra-class correlation” violates classical ordinary least squares (OLS) assumptions such as independence and common variance. Standard errors for team diversity or medical school level effects are likely to be underestimated with OLS. Thus, significance tests would overestimate the precision of information provided by the AMC-level variables (Kreft and De Leeuw 1998; Snijders and Bosker 1999). To avoid this problem, we applied multilevel modeling (MLM). Although MLMs are suitable for a variety of research questions in management research (Hitt et al. 2007), few papers to date have used this technique in the field of research productivity (Dundar and Lewis 1998; Porter and Umbach 2001).

In our study, we took a three-level MLM approach, nesting surgeons as micro-units within research teams and research teams within medical schools. Both team and medical school levels were considered to be macro-units. We used the following model

$$Y_{ijk} = \beta_{0ijk} + \beta_1 \cdot X_{1ijk} + \beta_2 \cdot X_{2ijk} + \dots + \beta_p \cdot X_{pijk} + \varepsilon_{ijk}$$

$$\text{with } \beta_{0ijk} = \beta_{0jk} + \alpha_1 \cdot Z_{1jk} + \alpha_2 \cdot Z_{2jk} + \dots + \alpha_p \cdot Z_{pj k} + u_{jk}$$

$$\text{with } \beta_{0jk} = \beta_{0l} + \lambda_1 \cdot W_{1k} + \lambda_2 \cdot W_{2k} + \dots + \lambda_p \cdot W_{pk} + v_k$$

where  $Y_{ijk}$  is the dependent variable, representing the  $i$ th surgeon’s research productivity in the  $j$ th research team of the  $k$ th medical school. The intercept for the  $j$ th research team is given by a fixed component  $\beta_{0ijk}$  and two random components  $u_{jk}$  and  $v_k$  that represent the random variation between teams within medical schools ( $u_{jk}$ ) and between medical schools ( $v_k$ ), whereas  $\varepsilon_{ijk}$  is the residual

variation at the surgeon level. The two random components  $\mathbf{u}_{jk}$  and  $\mathbf{v}_k$  are assumed to be normally distributed with zero mean.  $[X_{1ijk} \dots X_{pijk}]$  are a set of control variables at the level of surgeons that represent individual characteristics of each surgeon.  $[Z_{1jk} \dots Z_{pj k}]$  are the variables of interest at the level of research teams that represent team diversity.  $[W_{1k} \dots W_{pk}]$  are a set of control variables at the level of the medical schools that represent contextual influence factors in medical schools.  $[\beta_l \dots \beta_p]$ ,  $[\alpha_l \dots \alpha_p]$ , and  $[\lambda_l \dots \lambda_p]$  are the parameters to be estimated at the level of surgeons, the level of research teams, and the level of medical schools, respectively.

The dependent variables of this study, publications and citations, are nonnegative, integer count variables. When choosing an appropriate empirical model to examine how research productivity of surgeons is influenced, we had to consider that the distribution of our dependent variables was largely skewed to the right and contained a substantial proportion of zeros (24.2% for variable publications, 28.2% for variable citations).

Among the estimation techniques proposed to deal with these distributional characteristics are Poisson and negative binomial (NB) models, as well as zero-inflated Poisson (ZIP) and zero-inflated negative binomial (ZINB) models (Yau et al. 2003). To determine the best model fit among ZINB, ZIP, NB, and Poisson, we followed the steps proposed by Greene (1994) and Chou and Steenhard (2009).

Verified by a statistical test for overdispersion (Gourieroux et al. 1984), the negative binomial estimation provided a significantly better fit for the data than the more restrictive Poisson model. Also, other criteria commonly used to assess the fit such as Akaike's information criterion (AIC), Bayesian information criterion (BIC), and the log likelihoods indicated that the NB model had a better fit than the Poisson model (AIC 79944 vs. 34087; BIC 79958 vs. 34107;  $-2 \log$  likelihood, 79940 vs. 34081). To decide between the NB and the ZINB we applied the Vuong test (Vuong, 1989), which compares the conditional model with the true conditional distribution, to determine whether the NB model should be rejected in favor of the ZINB model. For number of publications, as well as for number of citations, the Vuong test suggested that the NB model could not be



rejected. We thus applied the NB specification for the publications as well as for the citations model.

For each variable we first estimated a univariate model assessing whether each variable was at least significant at  $P < 0.20$ . We then included the selected variables into the multivariate models testing for nonlinear effects using the likelihood ratio test. The GLIMMIX procedure of SAS version 9.1.3 was used for analysis.

## RESULTS

Table 2 depicts descriptive statistics and Table 3 presents results from regression models.

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Please insert Table 2 about here

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We first estimated a baseline model with individual and control variables only. In a second step, we included our diversity measures to explore whether team diversity influences individual research productivity. We performed the likelihood ratio test for the null hypothesis that the model without team diversity covariates has a better fit compared to the model with covariates for team diversity. The  $\chi^2$  statistic indicated strong significance ( $P < 0.001$ ) in favor of the model with diversity measures. Therefore, the parameter estimates of the diversity variables cannot be assumed to be zero.

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Please insert Table 3 about here

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In hypotheses 1 and 2 we suggested that diversity as disparity in hierarchical structure (H1) and in gender (H2) is to exert negative influence on individual research productivity. Hypothesis 1 was supported by the data: *Div-Hier* ( $P < 0.1$  in the publication model;  $P < 0.01$  in the citation model) shows that high Gini and thus high diversity lead to decreased individual research productivity. In both publication and citation models, hypothesis 2 has to be rejected because diversity in gender does not seem to have a significant effect on research productivity.

We hypothesized that variety in education has positive effects on individual productivity (H3). The results from our model basically support our hypothesis. Positive significant effects have been observed between variety of academic degrees (*Div-PhD*, *Div-MA*) and individual research productivity in both the publication ( $P<0.05$ ) and the citation models ( $P<0.05$ ). Variety in alma maters among team members, *Div-Edu*, at first significantly increases ( $P<0.01$  in the publication model;  $P<0.001$  in the citation model) but with rising diversity significantly decreases ( $P<0.05$  in the publication model;  $P<0.001$  in the citation model) research productivity of team members. The nonlinear relationship is illustrated in Figure 1. In the publication model, diversity in quality of education, *Div-Score*, has no significant effect on productivity. In the citation model, however, a positive relationship is found between diversity in quality of education and productivity ( $P<0.05$ ).

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Please insert Figure 1 about here

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Diversity in stars (*Div-Stars*), indeed, stimulates research productivity in both the publication ( $P<0.001$ ) and the citation model ( $P<0.001$ ) as proposed in hypothesis 4. Significant positive effects of diversity in experience (H5) could not be found in the data in the publication model. In the citation model, however, the data suggested a negative relation between age diversity and productivity and thus we had to reject hypothesis 5. There is significant proof that diversity in experience decreases productivity in the citation model ( $P<0.01$ ). Lastly, we were not able to draw any conclusions that diversity in nationality among team members (H6) had a positive effect on individual research productivity in both models.

The control variables generally have the expected signs. Having a PhD, a higher quality of education, being a foreigner and, supposedly due to pregnancy leaves, being male were associated with higher individual research productivity. Being an assistant or an associate professor compared to being a full professor and years in practice were associated with less individual research productivity. At the level of medical schools, grants, that is, the availability to have more resources increased the research productivity of team members, whereas teaching decreased their research productivity.

We tested the robustness of our findings in several ways. To begin with, we estimated models with other outcome measures such as the Hirsch Index or average citations per publication. The publication and the citation models showed a better fit than the models using Hirsch Index or average citations per publication as dependent variables. However, all relevant variables showed the same level of significance and the direction remained unchanged. Second, we tested other indices to operationalize our diversity variables such as Blau or Teachman indices, coefficient of variation, and mean Euclidean distance. Using log likelihood testing we identified the best diversity specification for each variable. Third, we re-estimated both models with quadratic and cubic specifications for each diversity variable. Those nonlinear effects that were significant remained in the model (*Div-Score* and *Div-Edu*). All other relevant variables remained unchanged. Finally, we re-estimated all models using different definitions of team size. We ran models with teams no smaller than 4 members ( $n = 415$  teams) and no smaller than 8 members ( $n = 294$  teams). The coefficients in the model with teams no smaller than 8 members lost slightly in significance, whereas the model with teams no smaller than 4 members showed hardly any changes. The models appear to be very robust to all performed sensitivity analyses. The robustness can be, in part, ascribed to the sample size that seems to be extensive compared to other studies in this field (Bland et al. 2005; Carayol and Matt 2004, 2006; Dunder and Lewis 1998; Lee and Bozeman 2005).

## **DISCUSSION**

### **Interpretation of Results**

In this paper, we introduce the concept of team diversity to individual research productivity. Although prior work on research productivity has acknowledged the need for analyzing departmental/laboratory structures to explain individual research productivity (Carayol and Matt 2004, 2006) existing studies lack theoretical corroboration. Our study, therefore, contributes to the literature in two ways. First, we use diversity theory to provide a theoretical framework for the leftover variance in individual research productivity controlling for factors on the individual level

as well as on the departmental level. Second, we contribute to diversity research by quantifying the effects of diversity on individual productivity, whereas most diversity-related studies focus only on group productivity (Harrison et al. 2002; Horwitz and Horwitz 2007; Kearney et al. 2009).

As proposed by diversity theories, for example, social categorization or distributive justice theory, disparity aspects of diversity appear to have negative effects on individual productivity. Although we cannot draw conclusions how diversity in gender (*Div-Sex*) influences productivity, diversity in hierarchical positions (*Div-Hier*) hinders individual productivity. One has to recall that diversity as disparity is at its maximum if one team member holds the lion's share in resources. Because the negative effects of competition (reduced communication, reduced sharing of information, withdrawal, etc.) seem to dominate in the context of academic research, equally distributed hierarchical positions among team members would be best.

Diversity as variety generally seems to have positive effects on productivity. Variety in team members in education (e.g., having PhD or MA degree), and thus uniform distributions of team members with and without a PhD/MA, increases individual productivity through a better distribution of knowledge within the group. For some characteristics, variety appears to have nonlinear effects on individual productivity, for example, diversity in graduation schools (*Div-Edu*), as shown in Figure 1. The inverted U-shape shows that diversity reaches an optimal level at a Gini of 0.22. For example, a team of 13 surgeons in our dataset had a Gini score of 0.22; the team consisted of three team members and two times two team members that graduated from the same university, whereas the other six team members graduated from six different universities.

It is likely that team members who are extremely diverse in *Div-Edu*, that is, each team member graduated from a different university, have problems in overcoming their interpersonal differences on observable dimensions that tend to be associated with lower levels of initial attraction and social integration (O'Reilly et al. 1989). Although discussions are a key element of academic research, a consensus needs to be reached to produce a publication at the end. In such a diverse team, no dominant line of thinking emerges in case of major controversy. Team members might even not share enough common values and beliefs to work closely together. As diversity of the

team gets closer to the optimum, the negative effects of being different from one another are leveled off by the benefits of heterogeneity in information resources. As diversity decreases below the optimum, the negative effects of social categorization start affecting the research process, that is, the gain in perspectives and knowledge no longer compensates for the isolation of dissimilar group members.

Interestingly, the number of publications for each team member does not differ whether the education of team members, that is, coauthors, was of similar, higher, or lesser quality as measured by *Div-Score*. This might be because a publication is mainly driven by only one or two authors and the other authors make much smaller contributions (Hollis 2001). These contributions do, however, have an impact on the quality of publications as can be seen in the citation model. Thus, if a team has only one member from an elite university, while all other members are from universities with a scientifically low ranking, the publications of each member of the team would be of lesser quality than if the team were more balanced in terms of the quality of education. This might be because a single team member with a high quality of education is less motivated to contribute to a publication driven mainly by one of the other team members if input into the work is less valuable to him or her.

Membership of a star scientist to a team, on the other hand, increases productivity. Although the arguments for quality of education might be also true for a star scientist, the case is slightly different. Although a researcher with high quality of education might find equals in other teams, star scientists will rarely do so. Therefore, the value of input from others might not matter that much to star scientists. Star scientists probably have the special ability of using other team members' capabilities to increase their own productivity when sharing knowledge (Nederhof and van Raan 1993).

Diversity in nationality did not have an effect on the number of publications or on citations. However, it might be that being a foreigner or not is too broad a measure to capture the positive or negative effect of diversity in the educational/cultural background of a person.

### **Limitations and Implications for Future Research**

Although we believe that we were able to cover the most important attributes related to diversity as variety, we were not able to gather data about team tenure, pay, resource access, or age that are meant to be important diversity attributes (Millikan and Martins 1996; Pelled et al. 1999). However, in a subsample of 300 surgeons we found that diversity in experience (*Div-YIP*) as used in the models is highly correlated with age. We also incorporated a number of organizational controls that we felt were influential in the special context of research at medical schools (e.g., teaching load and case productivity). However, other contextual factors have been previously applied in the literature<sup>1</sup> that we were not able to address, such as business strategy (Richard 2000), work climate (van de Vegt et al. 2005), or manager demographics (Jackson and Joshi 2004).

Further, it has to be recognized that the dependent variables in this study were measured over a 5-year period. We used such a long period to increase robustness of publication counts and to avoid bias through age, leave of absence, or sabbatical years. This approach, however, might also introduce bias. Surgeons who changed workplaces during the observation period could not be excluded for technical reasons. We also acknowledge that the organizational structures used in the analysis to explain outcomes might have been subject to change over time. To check whether these issues introduced bias to our study, we tested within a subsample of 300 surgeons to determine if significant differences occurred in productivity between 2004 to 2008 and 2009. We found that the average publication rate per year remained stable.

The definition of teams can also be problematic. Although two researchers independently identified potential teams we cannot guarantee that all members of a so-defined team are closely cooperating in reality. Errors might have also been introduced through the use of electronic databases such as the ISI Web of Science.

Finally, the study's focus on medical schools and, in particular, on surgeons raises questions about the generalizability of the findings because academic physicians are unique in their duty triad of

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<sup>1</sup> For a detailed review of contextual influence factors at multiple levels see Joshi & Roh, 2009.

patient care, research, and teaching. Despite these unique characteristics, we believe that our results can be transferred to other functional backgrounds and industry sectors because surgical research contains both process- as well as product-related research. In addition, previous studies have also used hospital-based surgical settings to analyze organizational phenomena and individual performance issues (Gittell et al. 2010; Huckman and Pisano 2006; Pisano et al. 2001).

## **CONCLUSIONS**

In this paper we sought explanations for differences in individual research productivity using theoretically developed team diversity measures while controlling for attributes on individual and organizational levels. We can draw several conclusions as to how our results are transferrable into practice and how potential research teams shall be composed to stimulate individual research productivity.

With regard to hierarchical structure of teams, managers are well advised to reduce resource concentrations in highly hierarchical teams. When teams are more balanced in terms of hierarchical positions resources are more adequately distributed and power struggles are less likely to occur. Managers should also pay attention to the educational background of their team members. It is beneficial for the individual productivity if team members are diversified in their educational background (different alma maters), in additional qualifications (MA/PhD degrees) as well as in the quality of education. However, if diversity is taken to an extreme, this will negatively affect productivity. Finally, managers should strive for membership of star scientists to their teams because this increases individual research productivity of all members.

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Figure 1. Relationship of Div\_Edu and research output

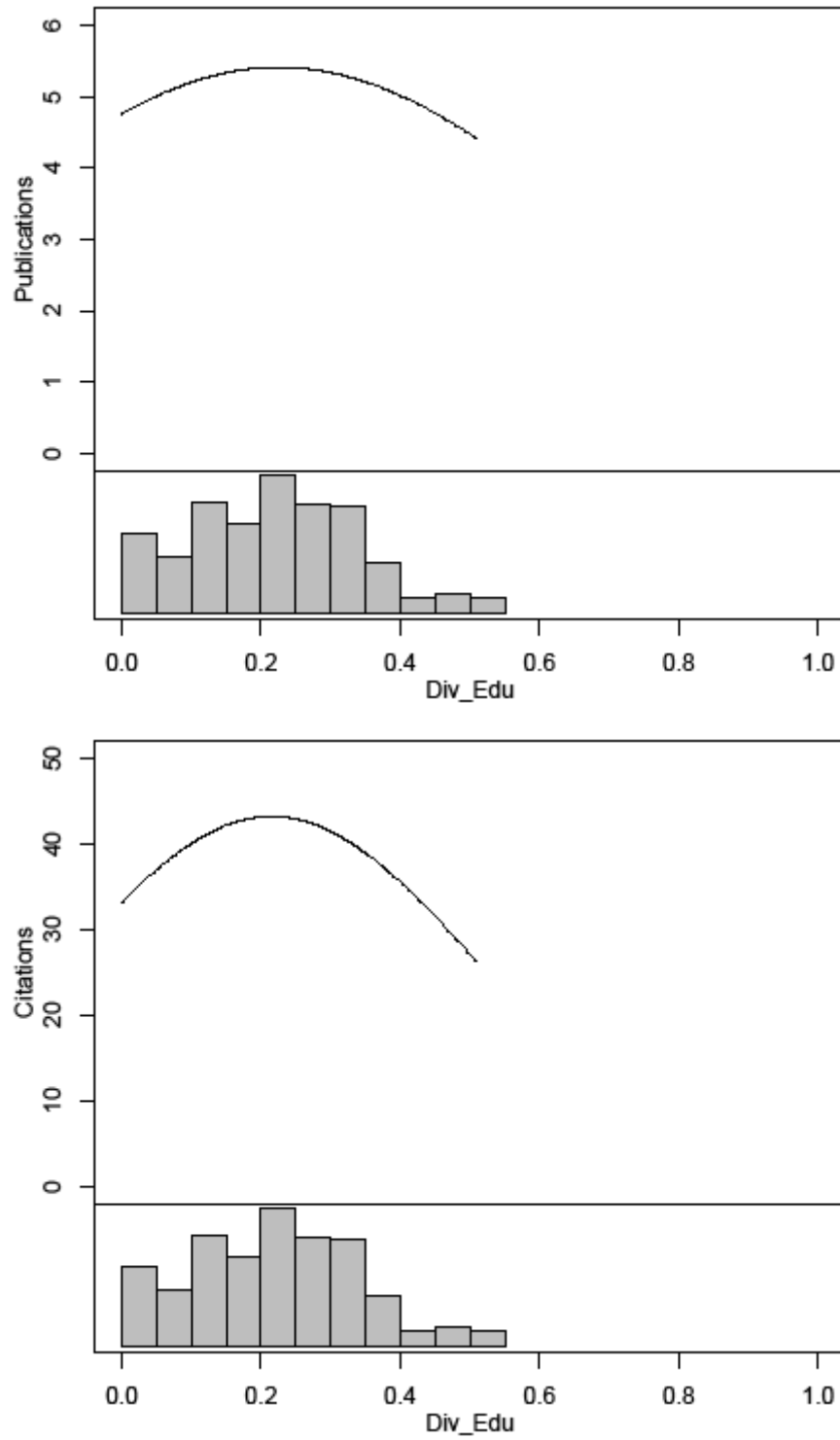


Table 1. Diversity measures and their interpretation

<b>Diversity Measure</b>	<b>Aspect of Diversity</b>	<b>Construct</b>	<b>Interpretation</b>
<i>Div-Hier</i> (H1)	Disparity	Gini Index	The higher the Gini, the more diversity
<i>Div-Sex</i> (H2)	Disparity	Modified Percentage	The higher the percentage, the higher diversity
<i>Div-Edu</i> (H3)	Variety	Gini Index	The higher the Gini, the smaller diversity
<i>Div-Score</i> (H3)	Variety	SD	The higher the SD, the higher diversity
<i>Div-PhD</i> (H3)	Variety	Modified Percentage	The higher the percentage, the smaller diversity
<i>Div-MA</i> (H3)	Variety	Modified Percentage	The higher the percentage, the smaller diversity
<i>Div-Star</i> (H4)	Variety	Modified Percentage	The higher the percentage, the smaller diversity
<i>Div-YIP</i> (H5)	Variety	SD	The higher the SD, the higher diversity
<i>Div-Nat</i> (H6)	Variety	Modified Percentage	The higher the percentage, the smaller diversity

SD, standard deviation.



Table 2. Descriptive statistics

<b>Variable</b>	<b>N</b>	<b>Mean</b>	<b>SD</b>	<b>Min</b>	<b>Max</b>
<i>Dependent Variables</i>					
Publications	5796	6.96	10.55	0.00	153.00
Citations	5796	71.56	154.77	0.00	3062.00
<i>Diversity Measures</i>					
<i>Div-Hier</i> (H1)	440	0.19	0.11	0.00	0.55
<i>Div-Sex</i> (H2)	440	0.44	0.35	0.00	0.97
<i>Div-Edu</i> (H3)	440	0.17	0.12	0.00	0.51
<i>Div-Score</i> (H3)	440	15.26	9.03	0.00	59.12
<i>Div-PhD</i> (H3)	440	0.77	0.25	0.00	1.00
<i>Div-MA</i> (H3)	440	0.95	0.11	0.33	1.00
<i>Div-Star</i> (H4)	440	0.98	0.07	0.33	1.00
<i>Div-YIP</i> (H5)	440	10.08	2.78	2.61	18.39
<i>Div-Nat</i> (H6)	440	0.69	0.27	0.00	1.00
<i>Controls Individual Level</i>					
YIP (years in practice)	5796	22.67	10.90	1.00	68.00
Assistant (0/1)	5796	0.44	—	0.00	1.00
Associate (0/1)	5796	0.26	—	0.00	1.00
Full (0/1)	5796	0.30	—	0.00	1.00
Sex (0-Female/1-Male)	5796	0.87	—	0.00	1.00
Foreign (0-native/1-foreign)	5796	0.15	—	0.00	1.00
Score (HEACCT-Ranking Score)	5796	28.20	17.59	0.00	94.82
PhD (0/1)	5796	0.13	—	0.00	1.00
MA (0/1)	5796	0.02	—	0.00	1.00
<i>Controls Medical School Level</i>					
Size (full-time faculty)	50	1310.18	550.31	421.00	3636.00
Teaching (students per faculty)	50	0.57	0.33	0.08	1.68
Productivity (admissions per faculty)	50	35.72	18.61	5.36	107.48
Grants (grants per faculty in million \$)	50	0.33	0.13	0.07	0.71

Note: Diversity measures are presented in order of hypotheses.

Table 3. Results from regression models

Variable	Publication Model			Citation Model		
<i>Independent Diversity Variables</i>	Coeff.		SE	Coeff.		SE
<i>Div-Hier</i> (H1)	– 0.396 <sup>t</sup>		(0.219)	– 0.770 <sup>**</sup>		(0.242)
<i>Div-Sex</i> (H2)	0.021		(0.069)	– 0.423		(0.077)
<i>Div-Edu</i> (H3)	1.469 <sup>**</sup>		(0.539)	3.102 <sup>***</sup>		(0.5967)
<i>Div-Edu*Div-Edu</i> (H3)	– 2.927 <sup>*</sup>		(1.236)	– 5.919 <sup>***</sup>		(1.367)
<i>Div-Score</i> (H3)	0.002		(0.003)	0.026 <sup>*</sup>		(0.011)
<i>Div-Score*Div-Score</i> (H3)	—		—	– 0.001 <sup>*</sup>		(0.000)
<i>Div-PhD</i> (H3)	– 0.210 <sup>*</sup>		(0.099)	– 0.285 <sup>**</sup>		(0.110)
<i>Div-MA</i> (H3)	– 0.539 <sup>*</sup>		(0.216)	– 0.583 <sup>*</sup>		(0.243)
<i>Div-Star</i> (H4)	– 2.055 <sup>***</sup>		(0.328)	– 2.585 <sup>***</sup>		(0.378)
<i>Div-YIP</i> (H5)	– 0.011		(0.009)	0.026 <sup>**</sup>		(0.010)
<i>Div-Nat</i> (H6)	– 0.075		(0.1010)	– 0.092		(0.114)
 <i>Controls Individual Level</i>						
YIP	– 0.357 <sup>***</sup>		(0.002)	– 0.041 <sup>***</sup>		(0.002)
Assistant	– 1.679 <sup>***</sup>		(0.048)	– 2.065 <sup>***</sup>		(0.05343)
Associate	– 0.831 <sup>***</sup>		(0.042)	– 1.011 <sup>***</sup>		(0.049)
Full		Reference			Reference	
Sex	0.288 <sup>***</sup>		(0.047)	0.195 <sup>***</sup>		(0.052)
Foreign	0.097 <sup>*</sup>		(0.043)	0.016		(0.049)
Score	0.003 <sup>***</sup>		(0.001)	0.004 <sup>***</sup>		(0.001)
PhD	0.383 <sup>***</sup>		(0.046)	0.728 <sup>***</sup>		(0.053)
MA	0.020		(0.095)	0.081		(0.111)
Subspecialties		included			included	
 <i>Controls Medical School Level</i>						
Size	0.000		(0.000)	0.000 <sup>*</sup>		(0.000)
Teaching	– 0.618 <sup>**</sup>		(0.201)	– 0.603 <sup>**</sup>		(0.211)
Productivity	0.004		(0.003)	0.004		(0.003)
Grants	0.952 <sup>**</sup>		(0.335)	1.292 <sup>***</sup>		(0.347)
 <i>Fit Statistics</i>						
–2 Res Log Pseudo-Likelihood		19113.19			24626.500	
Generalized $\chi^2$		6912.15			10722.660	
Generalized $\chi^2$ / DF		1.2			1.91	

<sup>t</sup> $P < 0.1$ ; \* $P < 0.05$ ; \*\* $P < 0.01$ ;  
\*\*\* $P < 0.001$

## **CHAPTER 5: Antecedents of individual-level R&D performance in exploratory, exploitative, and ambidextrous environments**

Von Reitzenstein C, Schultz C, Schreyoegg J (2010). Antecedents of individual-level R&D performance in exploratory, exploitative, and ambidextrous environments. *Organization Science* (under review).

## **ABSTRACT**

Using multi-level modeling, this article explores individual-level R&D performance and the influence exerted upon it by (a) organizational foci, such as exploration, exploitation, and ambidexterity, and (b) organizational mechanisms designed to mobilize and coordinate exploratory activities. Suggesting the presence of moderation effects across levels, we hypothesize that the impact of mobilization and coordination mechanisms on the R&D performance of individual employees varies according to organizational focus. Results based on a sample of 249 surgeons in 18 academic medical centers in the United States support our hypothesis, indicating that mobilization and coordination mechanisms can benefit R&D performance in some environments but hinder it in others. The results also suggest that these mechanisms are less effective in more complex environments, such as ambidextrous organizations. We conclude that mobilization and coordination mechanisms can shift objectives towards a desired goal but must be deployed carefully while taking organizational focus into account.

## **Keywords**

Exploration, exploitation, ambidexterity, mobilization and coordination mechanisms, individual-level R&D performance, multi-level modeling

## **INTRODUCTION**

Theorists and practitioners are still struggling to understand how organizations can best mobilize and coordinate exploratory activities while addressing exploitative operational requirements. The need to focus on both exploration and exploitation – in short, for ambidexterity – is widely recognized as a prerequisite for long-term success, and an increasing number of studies are examining the underlying organizational factors of ambidexterity and its impact on organizational performance. Although several seminal works on exploration, exploitation, and ambidexterity have been published to date, empirical findings addressing the effects of such different organizational

foci remain scarce (Groysberg and Lee 2009; He and Wong 2004; Mom et al. 2009). More specifically, there is an ongoing debate in the literature about whether ambidexterity undermines or enhances the generation of knowledge by employees (Adler et al. 1999). Unlike most of the more macro-level research on organizational ambidexterity, this debate assumes that individual-level outcomes are related to organizational factors. With this in mind, we take a multi-level approach in our study, aiming to deepen the understanding of organizational foci and their impact on individual-level exploratory activities, including R&D performance in particular.

Several researchers of ambidexterity have shown that traditional organizational incentives and processes support exploitative activities at the expense of exploratory goals. To succeed, they argue, ambidextrous organizations require mechanisms designed to mobilize and coordinate exploratory activities (Jansen et al. 2006), such as incentives and parallel processes. Although mechanisms like these are implemented at the organizational level, they usually influence behavior at the level of individual employees. Some researchers have recently suggested that here, too, a multi-level approach is needed to study organizational mechanisms and their micro-foundations (Abell et al. 2008; Felin and Foss 2005; Lichtenthaler et al. 2010; Teece 2007). A secondary aim of our study is therefore to analyze how mobilization and coordination mechanisms affect individual-level exploratory activities.

With an eye to the long tradition of contingency theory and the relevance of cross-level moderation effects (Keller 1994; Mone et al. 1998; Shenhar 2001), we expand upon the existing literature by taking account of the varying impact of mobilization and coordination mechanisms in the context of different organizational foci. More specifically, because the effects of any given mechanism may differ depending on an organization's focus, we examine whether particular mobilization or coordination mechanisms are helpful in one context while undermining individual-level exploratory activities in another.

Our empirical investigation is based on a sample of 249 surgeons from 18 academic medical centers (AMCs) in the United States (US). AMCs provide an excellent setting for research on

ambidexterity because surgeons working at these institutions must combine their exploratory activities – namely, research and development (R&D) – with daily clinical work. In the present study, we were able to combine three separate data sources. Individual-level R&D performance was measured by counting refereed journal publications that were attributable to each surgeon and had been indexed in the ISI Web of Science. For identifying and describing mobilization and coordination mechanisms, we relied on self-generated survey data. An AMC's organizational focus was determined by using external databases. In order to increase the validity of our results, we applied rigorous methods such as data envelopment analysis (DEA) and negative binomial regression.

Our paper proceeds as follows: In Section 2, we briefly present the conceptual background of organizational focus, organizational mechanisms, and multi-level research. In Section 3, we develop hypotheses accordingly. Section 4 presents the research setting and sample attributes, the analytical technique applied, and the constructs used as dependent, independent, and control variables. After reporting our empirical findings in Section 5, we discuss our results, point out our study's contributions and limitations, and consider the implications for future research and management practice in Section 6.

## **CONCEPTUAL FRAMEWORK**

### **Organizational focus**

In much of the literature, knowledge generation and issues related to R&D are discussed in terms of an organization's focus on exploration or exploitation. The general conclusion is that exploration increases long-term performance by helping to generate new knowledge and, in doing so, to develop and introduce innovations, whereas exploitation maintains short-term operational success by building on existing knowledge and extending current products and services (Bierly and Daly 2007; Danneels 2007; March 1991; Nerkar 2003). Exploration and exploitation, however, require fundamentally different and inconsistent architectures and competencies, creating

paradoxical challenges. A focus on exploration implies organizational behaviors characterized by search, discovery, experimentation, risk-taking, and innovation, whereas a focus on exploitation implies organizational behaviors characterized by refinement, implementation, efficiency, production, and a selection bias towards incremental improvement (Benner and Tushman 2003; Cheng and Van de Ven 1996; March 1991).

Recent research draws attention to the interplay between both types of organizational foci and suggests that these must be balanced and intertwined for sustained performance (Raisch et al. 2009). Because both exploration and exploitation contribute to organizational survival, the literature suggests that organizations would benefit from acting ambidextrously. Especially in demanding, uncertain and time-critical contexts – as is the case in hospitals – organizations must exploit existing knowledge and capabilities in order to fulfill operational needs (Jansen et al. 2006; Levinthal and March 1993). However, the well-being of organizations is not based solely on exploitation, as this would lead to inertia and a continued loss of competitive advantage (Levitt and March 1988). The need for ambidexterity is especially acute in organizations whose R&D output is a critical determinant of organizational performance, such as AMCs, where physicians have at least two duties to fulfill: patient care and research, which are frequently complemented by teaching duties (March 1991; O'Reilly and Tushman 2008).

### **Organizational mechanisms**

Mechanisms designed to mobilize and coordinate exploratory activities are considered to be important determinants of individual-level R&D performance (Jansen et al. 2009). They foster organizational learning (Gulati et al. 2000) and help to ensure that an organization's structures are able to accommodate its exploratory and exploitative needs. In contrast, organizational mechanisms that support only exploitative goals tend to eliminate variation in processes and outputs, leading to a focus on incremental improvement. Although this allows for leveraging of an organization's existing capabilities, it may also have a negative impact on learning (Hackman and Wageman 1995). Taking the cue from earlier studies on ambidexterity (Jansen et al. 2009; Mom et

al. 2009), we define (a) mobilization mechanisms as research-oriented incentive systems and (b) coordination mechanisms as the formalization of R&D processes. Because both mechanisms differ fundamentally from each other, however, we suggest that their impact on performance varies according to an organizational focus. Analyzing such cross-level effects requires a multi-level analytical design.

### **Cross-level effects**

To explain individual R&D output in complex organizations, we distinguish between multiple levels ranging from the individual to the organizational level. Considering that variables at different levels may complement or substitute effects across levels (Rothaermel and Hess 2007), several researchers have recently called for a cross-level examination of management topics in general (Drazin et al. 1999; Hitt et al. 2007), whereas others have advocated this approach specifically in the field of R&D management (Abell et al. 2008; Augier and Teece 2009; Gupta et al. 2006). The rationale for such approaches can be found in systems theory, which describes organizational phenomena as complex and dynamic systems within which different levels interact (Katz and Kahn 1978). In our study, we propose that the impact of mobilization and coordination mechanisms is shaped by organizational focus.

## **HYPOTHESIS DEVELOPMENT**

### **Exploration, exploitation, and ambidexterity**

We suggest that an organizational focus on exploration, which implies high research intensity, affects individual-level R&D performance positively. Organizations that focus on exploration are likely to set ambitious R&D performance goals, which – as long as they are specific, challenging, and measurable – are thought to have a positive impact on employee motivation (Locke et al. 1990) and R&D performance (Dvir et al. 2003; Tatikonda and Montoya-Weiss 2001). Furthermore, because individual-level R&D performance is visible to a researcher's colleagues,



peer pressure and social norms are thought to influence individual resource allocation (Sheremata 2000). Finally, a focus on exploration has substantial effects on team composition. Team members are selected based on their previous research output, and positive self-selection increases the probability that research-oriented professionals will apply for positions. New members rapidly adapt their norms and working styles through socialization processes. This is especially the case in knowledge-intensive, high-involvement environments, in which organizational foci have a considerable influence on individuals (Michel 2007). Based on these observations, we put forward the following hypothesis:

*Hypothesis 1: An organizational focus on exploration has a positive impact on individual-level R&D performance.*

Moreover, we suggest that an organizational focus on exploitation affects motivation, norms, and team composition in ways contrary to those seen in organizations with a focus on exploration. In an exploitative setting, managerial attention is centered on achieving operational goals. Here, research indicates that employees tend to be assigned duties related to operational production and do not have sufficient slack time or resources for research activity (Chen and Huang 2009; Daniel et al. 2004). Team composition and the socialization of young scientists are likely more operationally oriented in this setting, hampering the evolution of a research culture. Lastly, a focus on exploitation may also reduce tolerance towards risk among both management and employees (Benner and Tushman 2003). Based upon these observations, we propose our second hypothesis, as follows:

*Hypothesis 2: An organizational focus on exploitation has a negative impact on individual-level R&D performance.*

There is compelling evidence linking ambidexterity to both decreases and increases in individual-level R&D performance. Decreases have been attributed to the conflicting nature of exploration and exploitation, and may reflect trade-offs made to accommodate organizational limitations (Smith and Tushman 2005). Trade-offs can result from constraints in allocating limited resources

over exploratory and exploitative activities, and from the challenges associated with managing divergent cognitive models and organizational routines (Lavie et al. 2010). In turn, increases have been attributed to the benefits of combining separate operational domains (He and Wong 2004; Lavie and Rosenkopf 2006). For example, exploration may entail activities and processes associated with new product development, whereas exploitation may involve a distinct set of activities associated with modifying an existing product bundle (Voss et al. 2008). In such an environment, individuals must strive to maintain a balance between creativity, attention to detail, and quality so that innovative performance does not undermine quality and efficiency (Miron et al. 2004). This pressure to innovate – not only for innovation’s sake, but to increase the quality and efficiency of operational processes – helps to focus exploratory endeavors and increase R&D performance. A combination of exploratory and exploitative goals is also believed to support the integration of newly generated knowledge into operations. Although employees may be creative and generate new knowledge in an organization that does not focus on exploitation, this knowledge may be never implemented and thus never transformed into a solution or product. By the same token, there will be little new knowledge to integrate in organizations that do not focus on exploration (Gebert et al. 2010). Despite potential negative performance implications, we feel that the advantages of ambidexterity will, on the whole, outweigh these drawbacks, which leads to our third hypothesis, as follows:

*Hypothesis 3: An organizational focus on ambidexterity has a positive impact on individual-level R&D performance.*

### **Mobilization and coordination mechanisms**

Organizations generally create administrative mechanisms to promote certain behaviors (Burgelman 1983). In the case of ambidextrous organizations, researchers have identified several contextual antecedents of ambidexterity, including mechanisms designed to mobilize and coordinate exploratory activities (Jansen et al. 2009; Raisch et al. 2009). In order to mobilize individuals to contribute to exploratory activities, organizations create incentives (Clark and Wilson 1961). Incentives can have many effects, shifting objectives towards research, for example,

or resulting in extra working time devoted to research (Igalens and Roussel 1999). Organizational theorists have long acknowledged the importance of incentives in motivating an organization's employees, stressing that the political economy of an organization plays a major role in shaping organizational life and behavior (Ancona et al. 1999; Pfeffer 1990). Incentives have been demonstrated to be important tools for changing mindsets and modifying strategies, especially when transforming strategically diverse organizations (Kretschmer and Puranam 2008). As a result, we propose our fourth hypothesis, as follows:

*Hypothesis 4: Incentives designed to stimulate exploratory activities have a positive impact on individual-level R&D performance.*

A frequently used construct to conceptualize coordination is R&D process formalization, which expresses the degree to which rules, procedures, instructions, and communications are codified and enforced (Jansen et al. 2006; Khandwalla 1977). Although formalized R&D processes have been shown to increase overall organizational efficiency (Cooper 2008; Tatikonda and Rosenthal 2000), they have some important drawbacks. Prominent among these is a decrease in flexibility and learning ability (Bonner et al. 2002; Sethi and Iqbal 2008). Relying on rules and procedures has been shown to reduce the likelihood that individuals will deviate from structured behavior (Weick 1979), hampering experimentation and ad hoc problem-solving efforts (March et al. 1958). Along these lines, Sethi and Iqbal have shown that by decreasing project flexibility, formalization limits a firm's ability to learn from development projects (Sethi and Iqbal 2008). With its rules and regulations, the mechanistic approach inherent in formalized processes restrains developers' actions and thus does not work well in situations characterized by high levels of uncertainty (e.g. when quick and innovative solutions must be found to problems related to technology and the marketplace). Another important shortcoming of formalized R&D processes is the mismatch between codified rules and procedures and the outcomes of innovative activities. Highly innovative projects deviate by definition from standard practice and thus do not meet the strict and objective criteria used, for example, in stage-gate systems for new product development (Benner and Tushman 2003). Gate criteria are based on existing knowledge and driven by an organization's

short-term needs. Naturally, high-priority projects that are intended to pass each gate review are likely to be adapted to meet the review criteria, resulting in projects that are compatible with existing knowledge – and thus more incremental. In light of these observations, we put forward our fifth hypothesis, as follows:

*Hypothesis 5: Formalized R&D processes have a negative impact on individual-level R&D performance.*

### **Interactions between organizational focus and mobilization mechanisms**

The effectiveness of mobilization mechanisms, such as incentives, may be moderated by organizational focus, constituting a cross-level effect. Previous research suggests that incentives are intertwined with other structural mechanisms and that their impact varies depending on the environment in which they are applied (Kaplan and Henderson 2005; Kretschmer and Puranam 2008). In exploratory organizations, the motivation of individual employees is positively influenced by social norms and group pressure processes, which drive their research behavior. Moreover, incentives may have the unintended effect of crowding out high-value intrinsic motivations (Frey and Jegen 2001; James 2005). Incentives may also push individual activities in the wrong direction, creating inefficiencies. Similarly, incentivized goals may have negative effects if they are unrealistic or too specific (Ordonez et al. 2009), or if they exaggerate risk taking. In exploratory environments, incentives may also decrease risk taking (Gaba and Karla 1999; Hunton et al. 2008), reduce internal cooperation (Siemsen et al 2007; Wang and He 2008), or lead to opportunistic behavior (Fong and Tosi 2007). Based on these observations, we suggest that the effect of incentives on individual-level R&D performance will be moderated by organizational focus and that the effectiveness of incentives is reduced in exploratory environments. Our next hypothesis thus reads as follows:

*H6a: Incentives have a negative impact on individual-level R&D performance in exploratory environments.*

In contrast, we suspect that there is an increased need in exploitative environments for mobilization mechanisms to motivate employees to contribute to exploratory activities. Employees who have chosen to work in an environment where the organizational expectations are of an exploitative nature are probably driven by a desire to fulfill operational goals. With this in mind, we expect that external goals will have a positive influence on individual-level R&D performance in the absence of any other motivation to pursue research. Furthermore, we suspect that the incentives provided in an exploitative environment are less likely to crowd out intrinsic motivations (Amabile 1993; Dermer 1975; Roberts et al. 2006). Our next hypothesis can thus be stated as follows:

*H6b: Incentives have a positive impact on individual-level R&D performance in exploitative environments.*

To our knowledge, previous studies have not provided much insight into the effectiveness of incentives designed to stimulate exploratory activities in ambidextrous environments. However, three findings in the literature lead us to suggest that the impact of such incentives in ambidextrous organizations is minimal. First, research shows that individual characteristics, such as knowledge and experiences, determine the ability of employees to be successful at both exploratory and exploitative tasks (Amabile et al. 1996; Gupta et al. 2006). These characteristics are unrelated to specific reward systems. Second, achieving success in exploration while meeting an organization's exploitative needs requires a high level of intrinsic motivation among employees. Shalley and colleagues (2009) found that an employee's desire to grow and learn depends on his or her willingness to be involved in unstructured, uncertain and discrete tasks as those entailed in R&D. Employees with little desire to grow and learn professionally seek to avoid the frustrations associated with more complex jobs, which leads to a decrease in individual creativity and performance (Shalley et al. 2009). Incentive systems cannot create intrinsic motivation and may even interfere with an individual's desire to learn. Thirdly, ambidextrous organizations are characterized by very complex work environments. We therefore suggest that incentives designed to stimulate exploratory activities are not effective at addressing the varying needs of individual

researchers and might even steer them away from projects better suited to their specific skills.

These arguments support the following hypothesis:

*H6c: Incentives have a negative impact on individual-level R&D performance in ambidextrous environments.*

### **Interactions between organizational focus and coordination mechanisms**

The effectiveness of coordination mechanisms, such as formalization, may also be moderated by organizational focus, constituting yet another cross-level effect. In an exploratory environment, research is a fixed component of an employee's daily workload and there is less need for parallel processes and structures to aid in moving back and forth between operational routines and research duties (Li et al. 2008). Formal coordination with exploitative work is thus less important in this setting, allowing the negative effects of coordination mechanisms to come to the fore (cf. March et al. 1958 and Weick 1979, as described above). Because exploratory organizations generally conduct highly innovative projects, strong formalization is likely to increase the probability of failing to meet conservative, preset criteria, leading to the termination of promising projects. In summary, we believe that the negative effect of R&D process formalization on innovation, and therefore on publication performance, will outweigh any potential positive effects, leading us to the following hypothesis:

*H7a: Formalization has a negative impact on individual-level R&D performance in exploratory environments.*

In efficiency-driven organizations, individuals are averse to risk and thus any kind of experimentation because they have to focus on achieving operational goals and must avoid the potential short-term complexity entailed by research activities, even if conducting them is expected to lead to long-term benefits. These characteristics are especially prominent in hospitals (Nembhard et al. 2009). When integrating exploratory goals, employees are confronted with a number of challenges (Smith and Tushman 2005), including the need for paradoxical thinking (Gibson and Birkinshaw 2004) and for fulfilling multiple roles (Floyd and Lane 2000). To

stimulate research activity in this kind of environment, specific organizational instruments must be used alongside operational mechanisms to help employees move back and forth between a bureaucratic structure for routine tasks and an organic structure for non-routine tasks (Adler et al. 1999). Zollo and Winter, for instance, argue that formalization facilitates the generation of proposals to improve existing routines and can ensure that employees are able to move to exploratory tasks even under the pressure of everyday exploitative work (Zollo and Winter 2002). This leads us to formulate another hypothesis, as follows:

*H7b: Formalization has a positive impact on individual-level R&D performance in exploitative environments.*

Ambidextrous organizations are characterized by their capacity to exploit existing competencies and explore new opportunities simultaneously. Here, it is important to note that both organizational units and employees must be ambidextrous because the latter must balance their daily workload with exploratory activities (Gibson and Birkinshaw 2004). Formalization might be effective at helping employees achieve this balance (Jansen et al. 2006) but only if an organization is not highly complex. In organizations with a large number of different activities, actors, and interdependencies, we suggest that formalized processes will show unintended effects and should be modified in order to allow adaptive, self-organized solutions (Anderson 1999). Indeed, the positive effects of formalized, corporate-centric processes on interfunctional collaboration have been shown to diminish as the complexity of an organization increases (Martin and Eisenhardt 2010). Finally, individual creativity is demonstrably higher in situations where individuals may choose between creative and intervening tasks; this appears to be attributable to employees' abilities to reflect on exploratory activities during their operational duties (Madjar and Shalley 2008). These observations suggest the following hypothesis:

*H7c: Formalization has a negative impact on individual-level R&D performance in ambidextrous environments.*

Figure 1 summarizes the conceptual framework and hypotheses of our analysis. A plus sign (+) indicates that the relationship is hypothesized to be positive, and a minus sign (-) that the relationship is hypothesized to be negative.

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## **METHODS**

### **Setting and data**

To analyze the influence of organizational factors on individual-level R&D performance, it is vital to choose a setting where research activity can be traced back to individual employees. Unlike R&D firms, universities are a good example of such a setting because individual-level R&D performance can be measured in terms of publication output and the publications themselves can be attributed to individual authors (van Rijnsoever et al. 2008). Our empirical investigation is thus based on a sample of surgeons working at AMCs in the US. In contrast to other hospitals, AMCs are usually part of a university or medical school, and their mission to combine patient care (i.e. exploitation) and research (i.e. exploration) often leads to a trade-off between these two goals, reducing overall performance (Schreyögg and von Reitzenstein 2008). AMCs are thus perfectly suited for analyzing ambidexterity. Out of all medical fields, we chose the field of surgery for our analysis because surgeons require exceptionally specialized technological expertise for both patient care and research. Furthermore, the potential conflicts between exploratory and exploitative activities are most prevalent in the field of surgery, where the day-to-day work is, to a very high degree, manual and based on experience. In total, we surveyed 293 surgeons in 18 AMCs in the US using a self-designed questionnaire based on five-point Likert scales. During the preparatory phase of the study, we distributed a preliminary version of the questionnaire to 25 surgeons of various subspecialties, who subsequently provided us with feedback, which was used to refine the final survey instrument.

We contacted 70 US medical schools with the strongest research performance as ranked according to the Higher Education Evaluation and Accreditation Council of Taiwan (HEEACT 2009). 18



medical schools agreed to participate in the survey, five of which were ranked among the top 20 medical schools in the US (HEEACT 2009). In these 18 medical schools we distributed our questionnaire to 550 surgeons. 293 surveys were completed, which corresponds to an individual response rate of 53%. Of these responses, six had to be excluded due to missing data, resulting in a total of 287 useable questionnaires. Subsequently, data from the survey were combined with objective data on participating surgeons' R&D performance, which we measured by counting refereed journal publications that were attributable to each surgeon and had been indexed on the ISI Web of Science. Because 38 surgeons had not included their names on the questionnaire, data on a total of 249 surgeons were ultimately included in our analysis.

Of these surgeons, 209 were men and 40 were women, and the mean age of the sample was 48.1 years. We divided the sample into four subgroups according to subspecialty, assigning 107 to the general surgery group (SURG; including transplant surgery and surgical oncology), 59 to the orthopedic surgery group (ORTHO; including trauma surgery), 29 to the cardiothoracic surgery group (CARDIAC), and 54 to the miscellaneous subspecialties group (OTHER; including neurological, plastic, pediatric, ophthalmological, urological, head and neck, gynecological, and otolaryngological surgery).

## **Measures**

### ***Individual-level R&D performance***

Although indicators such as technology licenses have recently attained prominence in innovation research (Chang et al. 2009; Nelson 2009; Powers and McDougall 2005; Thursby and Thursby 2002), patents and publications have remained the indicators of choice. In the present study, we focus on publications because these represent an essential part of virtually any academic career in medicine and the natural sciences (Dundar and Lewis 1998; Neill 2008; Olson 1994). While publication counts are a valid proxy for research activity, citations are increasingly viewed as a measure of research quality (He et al. 2009). We therefore used total publication and citation

counts in the present analysis as the dependent variable to proxy for the R&D performance of each participating surgeon. Due to the lack of standardized authorship conventions that would have allowed us to estimate the extent of a surgeon's contribution to each paper, we decided to use the total publication and citation count regardless of the position at which the surgeon's name appeared in each author list. Publication and citation records were obtained from the ISI Web of Science, which covers more than 10,000 journals from over 100 scientific disciplines. Because the errors inherent in electronic databases necessitate stringent quality control procedures (Hood and Wilson 2003), we identified participating surgeons by matching their departments and institutions in addition to their names. To reduce age biases and to increase robustness, we selected a 6-year period (2005 through 2010), counting all articles in which the participating surgeons appeared as authors.

### ***Exploration, exploitation, and ambidexterity***

Data to model measures of exploration, exploitation, and ambidexterity were collected at the AMC level by using external databases such as the American Hospital Association (AHA) Annual Survey Database (American Hospital Association 2007) and the Medical School Profile System (MSPS) (American Association of Medical Schools 2009). To model the variable "exploration", we used the ISI Web of Science to determine publication counts for all department members during the same five-year period (i.e. 2004 through 2008); the average number of publications per department in each AMC serves as a proxy for a focus on exploration. In turn, the variable "exploitation" represents the technical efficiency of an AMC with respect to the delivery of patient care, with high efficiency serving as a proxy for a focus on exploitation. Efficiency scores were calculated using data envelopment analysis (DEA), which is described in more detail below. Because surgeons who completed the survey were also included in the average publication measures, we performed sensitivity analyses, excluding survey respondents from mean calculations to address potential endogeneity issues.

Lastly, we identified ambidextrous AMCs that were both efficient and research-intensive and assigned them to a binary variable that we refer to as “ambidexterity”. AMCs that belonged to the top 50% of the sample in terms of exploration and exploitation were assumed to be ambidextrous, resulting in a total of four ambidextrous AMCs (22%) and 30 surgeons (12%) working at ambidextrous institutions. When conducting a sensitivity analysis to test the validity of the proposed 50% boundary, the model lost explanatory power as we restricted and extended the 50% cutoff line and the “ambidexterity” variable became insignificant.

### ***Mobilization and coordination mechanisms***

In our survey, we analyzed incentives (i.e. a mobilization mechanism) and formalization (i.e. a coordination mechanism) using five-point Likert scales with items ranging from (1) “strongly disagree” to (5) “strongly agree”. Survey items related to incentives were derived from the Work Preference Inventory (WPI) (Amabile et al. 1994), whereas those related to formalization were derived from well-established scales on new product development (NPD) process formality (Cooper et al. 2003; Griffin 1997; Kleinschmidt et al. 2007).

Two distinct factors were identified through exploratory factor analysis. Results from a confirmatory factor analysis indicated adequate fit for our measures of mobilization and coordination (GFI = .95, SRMR = .055, RMSEA = .07, CFI = .96, IFI = .96;  $\chi^2 = 45.81$  [df = 19]). The first factor, which we refer to as “incentives”, expresses the degree to which surgeons’ research activities are driven by incentives such as money, recognition, or career perspectives. We asked surgeons if they worked on developing new solutions (1) “to impress [their] colleagues” [.66], (2) “to gain scientific recognition” [.86], “to enhance [their] career prospects” [.84], and (4) “to receive financial rewards” [.56]. The four items loaded on a single factor, having an eigenvalue greater than 1 and accounting for 56% of the variance ( $\alpha = .73$ ).

The other factor, which we refer to as “formalization”, represents participating surgeons’ perception of the formal organization of research projects and the degree to which such projects are

formalized in their place of work. To capture formalization, we asked surgeons to indicate the extent to which (1) “[they] can rely on a formal innovation process, i.e. a standardized set of stages and ‘go/no-go’ decisions that guide innovation activities from idea to launch” [.86], (2) “[their] AMC has an innovation process that clearly lists and defines specific activities (e.g. laboratory tests, medical trials) for each stage of the process” [.90], (3) “[their] AMC has clear and well-communicated criteria for ‘go/no-go’ decisions and significant resource adjustments” [.91], and (4) “[they] receive constructive feedback regardless of whether further work is done on an idea” [.68]. The four items loaded on a single factor, having an eigenvalue greater than 1 and accounting for 72% of the variance ( $\alpha = .86$ ).

### ***Control variables***

To reduce the likelihood of unobserved heterogeneity among surgeons, we controlled for several attributes. First, we looked for differences between the surgeons’ subspecialties, specifically the groups SURG, ORTHO, CARDIAC, and OTHER as defined in the previous section. Lastly, we controlled for age to reduce career-stage biases.

### **Empirical model**

Our empirical model is based on the assumption that the R&D output of surgeons is a function of individual surgeon characteristics and attitudes, as well as of the general strategies followed by AMCs, which are determined by hospital management. It is important to recognize that whereas individual characteristics and attitudes may differ from surgeon to surgeon, AMC strategies apply to all surgeons employed at a given AMC. As a result, observations across surgeons are not independent. This intra-class correlation violates classical OLS assumptions such as independence and common variance. Moreover, standard errors for AMC-level effects are likely to be underestimated with OLS. Significance tests would therefore lack robustness, overestimating the precision of information provided by the AMC-level variables (Kreft and De Leeuw 1998; Snijders

and Bosker 1999). To avoid this problem, we applied multi-level modeling. The structure of multi-level modeling has been described in detail by Gupta and colleagues (2006) and Hitt and colleagues (2007). In our study, we took a multi-level modeling approach with two levels, nesting surgeons as micro units within hospitals, which were, in turn, considered to be macro units. We used the following model

$$y_{ij} = \beta_{0j} + \beta_1 x_{ij} + \beta_2 z_j + \varepsilon_{ij}$$

$$\beta_{0j} = \beta_0 + u_j$$

where  $y_{ij}$  is the dependent variable, representing the  $i$ th surgeon's R&D performance. The intercept for the  $j$ th AMC is given here as a fixed component  $\beta_0$  and a random component  $u_j$ , which indicates the random effects among AMCs on the dependent variable. Moreover,  $x_{ij}$  is a vector of explanatory variables at the surgeon level and represents formalization and incentives, as well as the control variables, whereas  $z_j$  is a vector of explanatory variables at the hospital level that represents a focus on exploration, exploitation, or ambidexterity. The random term  $\varepsilon_j$  represents the unexplained variation for surgeons within an AMC. The random terms  $u_j$  and  $\varepsilon_j$  are assumed to be normally distributed with zero mean. We grand-mean-centered all independent and control variables to facilitate interpretation of moderation effects (Aiken et al. 1991).

The dependent variables in the present analysis – namely, publications and citations – are non-negative, integer count variables. When choosing an appropriate empirical model to examine the impact of our covariates on the R&D performance of surgeons, we had to consider that the distribution of our dependent variables was skewed strongly to the right and contained a substantial proportion of zeros (16%). Several estimation techniques have been proposed in the literature to deal with distributional characteristics like these, including Poisson and negative binomial (NB) models, as well as zero-inflated Poisson (ZIP) and zero-inflated negative binomial (ZINB) models (Yau et al. 2003). To determine the best fit among ZINB, ZIP, NB, and Poisson, we followed the steps proposed by Greene (1994) and Chou and Steenhard (2009).

As verified by a statistical test for overdispersion (Gourieroux et al. 1984), the negative binomial estimation provided a significantly better fit for the data than the more restrictive Poisson model. To find the better fit between NB and ZINB, we applied the Vuong test (Vuong 1989), which compares the conditional models with the true conditional distribution, to determine whether NB should be rejected in favor of ZINB. For both dependent variables, the results of the Vuong test suggested that the NB and ZINB models were equally efficient. Because other common criteria of fit, such as Akaike's information criterion (AIC) and Bayesian information criterion (BIC), also indicated that NB was superior in this regard, we chose to use this model throughout our analysis.

### **Data envelopment analysis**

To determine the relative efficiency of patient care, we employed DEA – the most frequently used approach to measuring efficiency in the hospital sector (Hollingsworth 2003). A linear programming technique for evaluating the relative efficiency of individual organizations based on observed data, DEA allows multiple inputs and outputs to be considered simultaneously, which is particularly well-suited for measuring the efficiency of hospitals. The relative efficiency of an organization is defined as the ratio of the weighted sum of its outputs to the weighted sum of its inputs. The weights are not pre-assigned but rather determined by the model, thus avoiding any bias resulting from subjectively assigned weights. DEA assesses the efficiency of organizations in two stages. First, the location and the shape of the efficiency frontier are determined based either on organizations that use the lowest input mix to produce their outputs or on organizations that achieve the highest output mix given their inputs. The efficiency frontier is constructed by joining these observations and all linear observations in the input-output space. In the present study, we used an input-oriented DEA approach to address the following question: “To what extent can the input factors, defined as supplies and labor, be reduced proportionally without changing the output quantities of hospitals, defined as the number of cases?” Second, DEA measures inefficiency as the radial distance from the inefficient unit to the frontier and produces an efficiency score that reflects the relative efficiency of each unit (Cooper et al. 2004).

To reduce sensitivity to different DEA model specifications and to minimize problems resulting from outliers in small samples, DEA efficiency scores are corrected using a bootstrapping procedure. The procedure applied in the present study follows the bootstrap approach developed by Simar and Wilson (1998). Our bias-corrected scores were derived from 250 bootstrap iterations, which allowed us to estimate a robust regression model, including DEA efficiency scores represented by the “exploitation” variable in the regression analysis (Simar and Wilson 1998).

When selecting inputs and outputs, we followed the example of other studies that have developed DEA frameworks for measuring hospital efficiency (Burgess Jr and Wilson 1996; Pilyavsky et al. 2006). In total, we considered five inputs and one output. The first input variable is the amount spent on supplies per year including operational expenses, but excluding payroll, capital, and depreciation expenses. Taking into account the importance of labor resources in the hospital production process, we included the number of full-time equivalents for the following personnel categories as additional input variables: total medical faculty, nursing staff, technical staff, and other staff members. The output variable reflects the number of treated inpatient cases per year in all hospitals associated with each AMC.

## RESULTS

Table 1 shows our descriptive statistics and bivariate correlation matrix, while Table 2 presents the results of our regression analysis. The surgeons were well distributed across the various subspecialties, represented a broad range of ages (32–73 years), and included individuals who were very innovative and those who were not. The goodness-of-fit tests indicated that the chosen model fit the data very well.

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Please insert Table 1 about here

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We began by estimating baseline models with individual- and organizational-level variables, as well as control variables (Models 1 & 3). The subsequent models (Model 2 & 4) included

interaction terms to explore whether organizational focus has moderating effects on incentives and formalization. We performed Wald tests for the null hypothesis, which states that the parameters of the models with interaction effects do not differ from those of the models without interaction effects (i.e. the parameters of the squared variables are assumed to be zero). Because the chi-square statistic indicated strong significance ( $P < 0.001$ ) for the former compared to the latter models, the parameters of the interaction variables could not be assumed to be zero and the null hypothesis had to be rejected.

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Please insert Table 2 about here

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In hypotheses 1, 2, and 3, we suggested that organizational focus has a varying impact on individual R&D performance. Exploration was hypothesized to have a positive (H1) and exploitation a negative (H2) impact on individual R&D output, which was supported by the results of our analysis, with  $P$  values  $< 0.01$  and  $< 0.001$ , respectively, in the publication model and  $P$  values  $< 0.001$  in the citation model. In hypothesis 3, we suggested that an ambidextrous organizational focus stimulates individual-level R&D performance, which was also supported by our findings ( $P < 0.05$  in the publication model;  $P < 0.001$  in the citation model). In hypothesis 4, we proposed that individual-level R&D performance is negatively affected by the coordination mechanism “formalization” but is positively affected by the mobilization mechanism “incentives”. Both hypotheses were supported by our results in publication and citation models ( $P < 0.001$ ).

Further, we posited that organizational focus moderates the impact of mobilization and coordination mechanisms on individual-level R&D performance. Hypotheses H6a and H6b, which stated that the impact of incentives on R&D performance is weakened by an exploratory focus, but strengthened by an exploitative focus, were supported by the results of our analysis in both models ( $P < 0.001$ ). The hypothesized negative moderation effect of ambidextrous organizations on the impact of incentives on individual R&D performance was not supported by the results (H6c).

In hypothesis 7a, we suggested that formalized processes affect individual-level R&D activity negatively in organizations with a focus on exploration. This was not supported by our data,



whereas the interaction between formalization and an exploitative focus on individual R&D activity is indeed negative (H7b). Our hypothesis that there are negative interaction effects between formalization and ambidextrous focus on individual-level R&D performance (H7c) was supported by our results for both models ( $P < 0.05$ ).

We checked the robustness of our results in several ways. First, we tested alternative count data specifications, including Poisson and ZINB models. The modifications had very little impact on the coefficients, and all effects remained significant. Second, we re-estimated the models by using publication and citation counts for the years 2008 through 2010 only, thus addressing concerns that publication activity may not have resulted directly from the strategies examined by our questionnaires (which were completed in 2007 and 2008), or that strategies may have changed over time. Importantly, coefficients did not change their direction, and the level of significance changed only marginally throughout the estimations. Third, we ran several sensitivity analyses to determine whether the specification of ambidexterity measures influenced our results. The results remained stable. Finally, we modified the variable “exploration” by excluding survey respondents from the measure “publications per faculty” to minimize bias, and subsequently re-estimated the models. Again, our results remained robust. We therefore believe that the findings of our study are valid and reliable.

## **DISCUSSION AND CONCLUSION**

In the present study, we explored the individual-level R&D performance of 249 surgeons at 18 AMCs in the US and the influence exerted upon it by (a) organizational focus and (b) two organizational mechanisms thought to mobilize and coordinate exploratory activities. Organizational focus was defined as being exploratory, exploitative, or ambidextrous, and incentives and formalization were chosen as examples of mobilization and coordination mechanisms, respectively. At the outset of the analysis, we suggested the presence of cross-level moderation effects, hypothesizing that the impact of incentives and formalization on individual-level R&D performance varies according to organizational focus.

Although prior research has suggested that exploratory, exploitative, and ambidextrous foci have different effects on an organization's performance (e.g. Gibson and Birkinshaw 2004; He and Wong 2004; Lavie et al. 2010; Lubatkin et al. 2006), our study is among the first to provide valid empirical evidence of the different effects of organizational foci on individual-level R&D performance. In doing so, we respond to recent calls to consider the individual level when analyzing the performance implications of ambidexterity, especially in an R&D setting (Gupta et al. 2006; Jansen et al. 2005; Raisch et al. 2009; Simsek 2009). Lastly, with our study and the concept behind it, we contribute to an understanding of how individual-level R&D behavior is affected by different organizational mechanisms in organizations with varying foci.

The advantages of multi-level methods allowed us to develop a framework to analyze these cross-level effects in addition to the impact of organizational focus, incentives, and formalization. We found that ambidexterity had a positive impact on individual-level R&D performance, as did an exploratory focus. An exploitative focus, however, had a negative impact on individual R&D performance. Of course, because individual-level R&D performance is intrinsically related to exploration, it is not surprising that exploratory environments led to an increase, and exploitative environments to a decrease, in this outcome measure. However, although empirical studies on the outcomes associated with balancing these foci is abundant, their results have been mixed, providing only anecdotal evidence of positive performance implications (Lavie et al. 2010). In particular, our findings clearly indicate that ambidexterity has a positive impact on individual-level R&D performance. Moreover, our data show that without taking organizational focus into account, individual-level R&D performance was positively affected by incentives but negatively affected by formalization – both of which are straightforward findings that support assertions made in previous studies about the impact of such mechanisms.

In addition, we were able to confirm our hypothesis that the impact of incentives and formalization on individual-level R&D performance is moderated by organizational focus. Indeed, whereas formalization had a negative impact on individual-level R&D performance when organizational focus was not taken into account, our data show that formalization had a positive impact on

performance in exploratory environments and an even stronger positive impact on performance in exploitative environments. We thus conclude that formalized R&D processes can foster individual-level R&D performance, especially if an organization focuses on immediate operational outcomes. It would therefore seem that formalization, due to advantages such as increased overall organizational efficiency (Cooper 2008; Tatikonda and Rosenthal 2000), is best deployed in settings with a clear organizational focus. In ambidextrous organizations, however, formalization had a negative impact on individual-level R&D performance. We attribute this finding to the drawbacks of formalization in complex environments (Anderson 1999), where a decrease in flexibility and learning ability (Bonner et al. 2002; Sethi and Iqbal 2008), a reluctance to deviate from structured behavior (Weick 1979), and a avoidance of experimentation and ad hoc problem solving (March et al. 1958) might be more likely to appear.

Moreover, our analysis shows that the impact of incentives varies according to organizational focus. Whereas incentives were not relevant in exploratory environments, they were an effective instrument to foster individual-level research efforts in exploitative environments. This finding suggests that in organizations which already have an exploratory focus, research-oriented incentives may have the unintended effect of crowding out high-value intrinsic motivations, or that incentives create inefficiencies by propelling individual activities in the wrong direction (Frey and Jegen 2001; James 2005).

Our study has a number of important limitations. Chief among these is our use of total publication and citation counts as the sole measures of R&D output. Analyzing journal articles is fraught with difficulties related to authorship, journal quality, and publication type. Although our analysis does not differentiate between articles based upon the order of authorship, we initially considered the number of articles with first authorship as a dependent variable. Doing so resulted, however, in a sample that was too small for statistical evaluation. Future studies on similar topics might benefit from including additional measures of R&D output, such as patent counts. Unfortunately, using patent counts was not a solution in our case, as a search in our sample using the PATSTAT 2009 database revealed that 225 patents had been filed by 34 surgeons, which also would have been too

small for meaningful study. Another shortcoming is related to the issue of journal quality, which we were unable to address in our publication model. Citation counts, however, allowed for some quality assessment because higher-ranked journals (and, generally, higher-quality research) are presumably cited more frequently.

Additionally, although we found that AMCs were a suitable environment for testing our hypotheses, the present study's focus on medical, and particularly on surgical, research raises questions about the generalizability of our findings. Academic physicians are unique in their triad of patient care, research, and teaching duties. We are nevertheless convinced that our results can be transferred to other functional backgrounds and industry sectors because previous studies have also successfully used hospital-based surgical settings to analyze organizational phenomena and individual-level performance issues (Gittell et al. 2010; Huckman and Pisano 2006; Pisano et al. 2001).

In conclusion, many studies suggest that resolving the conflict between exploration and exploitation can improve organizational performance by delivering the efficiencies inherent in intense exploitation without sacrificing adaptability – in other words, combining steady exploitation with vibrant exploration (Gibson and Birkinshaw 2004; March 1991). Our findings show that ambidexterity may increase individual-level R&D performance, thus leading to an increase in an organization's overall performance. However, as our findings and previous research emphasize, implementing ambidexterity is clearly a delicate task (Lavie and Rosenkopf 2006; Lavie et al. 2010; Levinthal and March 1993; O'Reilly and Tushman 2008). Only when there is an optimal fit between focus and internal structure can an organization's performance be maximized (Greenwood et al. 2005; Hitt et al. 2001). Formal organizational mechanisms can help motivate and coordinate exploratory activities in spite of operational needs (Jansen et al. 2009) but must be implemented carefully with respect to the organizational focus. Our findings suggest that organizational mechanisms should be employed primarily in organizations that focus on exploitation. In this environment, both incentives and formalized R&D processes are likely to have positive effects.

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Figure 1. Proposed model

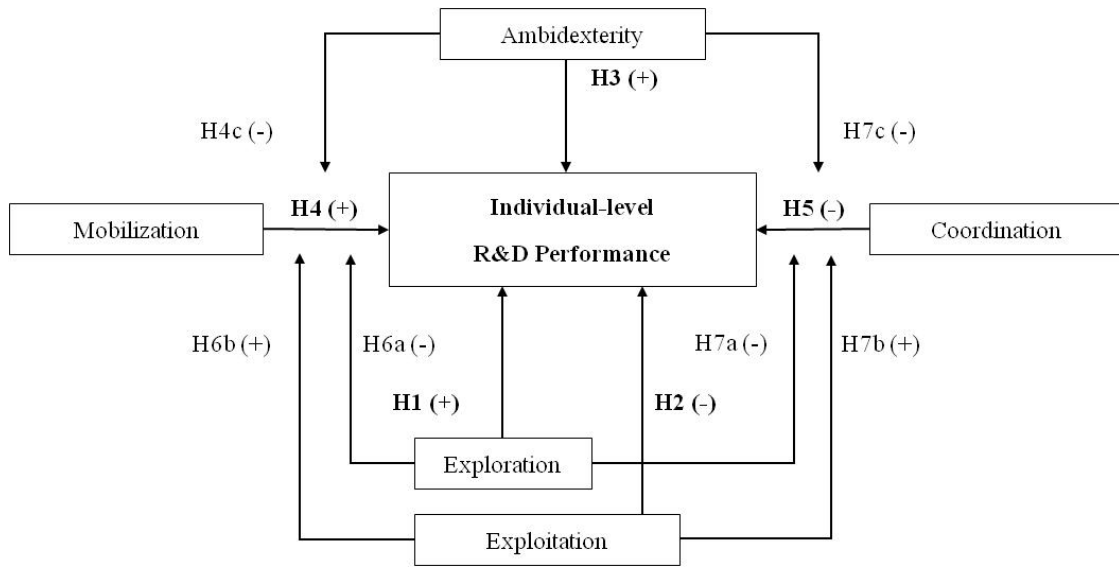


Table 1. Descriptive statistics and bivariate correlation matrix

	Variable	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10	11
<i>Individual-level R&amp;D performance</i>																
1	Publications	7.14	11.16	0.00	61.00	-										
2	Citations	68.34	138.37	0.00	1127.00	0.73	-									
<i>Organizational focus</i>																
3	Exploration	5.54	2.83	2.06	14.82	0.26	0.22	-								
4	Exploitation	0.72	0.12	0.50	0.91	-0.09	-0.07	-0.30	-							
5	Ambidexterity	0.18	0.40	0.00	1.00	0.13	0.07	0.40	0.41	-						
<i>Mobilization and coordination mechanisms</i>																
6	Incentives	2.68	0.82	1.00	5.00	0.03	-0.01	0.09	-0.07	0.07	-					
7	Formalization	2.43	0.89	1.00	5.00	0.00	0.05	0.02	0.04	0.08	0.11	-				
<i>Controls</i>																
8	Age	48.18	9.52	32.00	73.00	0.13	0.13	0.00	0.02	0.00	-0.01	-0.19	-			
9	Surg	0.43	0.50	0.00	1.00	-0.07	0.00	0.01	0.11	0.16	0.11	0.01	0.03	-		
10	Cardiac	0.12	0.33	0.00	1.00	-0.01	0.01	-0.01	-0.10	-0.11	-0.06	0.02	0.02	-0.32	-	
11	Ortho	0.23	0.42	0.00	1.00	0.00	-0.03	0.00	-0.01	-0.01	-0.03	0.00	0.00	-0.48	-0.21	-
12	Other	0.21	0.41	0.00	1.00	0.07	0.02	0.00	-0.03	-0.09	-0.04	-0.04	-0.06	-0.45	-0.19	-0.29
<i>n</i> = 249; All correlations above  0.10  are significant at <i>P</i> < 0.05																

Table 2. Results of the random-effects negative binomial regression

Variable	Publications		Citations	
	Model 1	Model 2	Model 3	Model 4
Intercept	1.86***	1.81***	4.36***	4.12***
<i>Organizational focus</i>				
Exploration (H1)	0.04***	0.11**	0.29***	0.06***
Exploitation (H2)	-0.25***	-6.38***	-0.88***	-3.41***
Ambidexterity (H3)	0.77***	0.66*	0.16***	0.47***
<i>Mobilization and coordination mechanisms</i>				
Incentives (H4)	0.17***	0.18***	0.11***	0.08***
Formalization (H5)	-0.05	-1.28***	-0.77***	-0.82***
<i>Interaction effects</i>				
Exploration × Incentives (H6a)		-0.07***		-0.05***
Exploitation × Incentives (H6b)		0.74***		0.63***
Ambidexterity × Incentives (H6c)		-0.09		-0.27
Exploration × Formalization (H7a)		0.07***		0.06***
Exploitation × Formalization (H7b)		1.24***		0.5***
Ambidexterity × Formalization (H7c)		-0.21*		-0.13*
<i>Controls</i>				
Age	0.03***	0.03***	0.04***	0.03***
Surg (Reference)	0.0	0.0	0.0	0.0
Cardiac	-0.19*	-0.25**	-0.58***	-0.58***
Ortho	0.17	-0.05	-0.11***	-0.11***
Other	-0.24**	-0.23**	-0.09***	-0.13***
<i>Fit statistics</i>				
Log likelihood	-1477.03	-1435.32	-14051.48	-13724.22
LR chi-square (DF)	153.27 (11)	195.36 (17)	2640.91(11)	2967.16(17)
Improvement (Wald test; Chi2 (4))		42.09***		327.26***
Comparison		Model 1		Model 3
<i>n</i> =249 Note: Results are presented on the log scale because we used a log link function.				
* <i>P</i> <0.05				
** <i>P</i> <0.01				
*** <i>P</i> <0.001				

**CHAPTER 6: A model of individual ambidexterity and resource access  
as drivers of individual R&D performance**

Von Reitzenstein, C (2010). A model of individual ambidexterity and resource access as drivers of individual R&D performance. Working Paper.

## **ABSTRACT**

Using multi-level modeling, this article explores individual R&D performance and the influence exerted upon it by individual ambidexterity while controlling for organizational ambidexterity. The article also analyses how the relation between individual R&D performance and individual ambidexterity is moderated by access to internal and external resources. We hypothesize that individual ambidexterity positively affects individual R&D performance. Further we assume that internal resource access positively moderates this relation while external resources have a negative impact on the individual ambidexterity–performance relation. Results based on a sample of 332 surgeons in 20 academic medical centres in Germany support our hypothesis. We conclude that managers should consequently ensure that their creative workforce acts ambidextrously, and thus is not only engaged with explorative tasks but is also involved in exploitative activities. Further, managers should make sure that the appropriate resources are provided to individuals who attempt to combine exploration and exploitation. Ambidextrous individuals benefit most from access to internal resources, while external resources are more efficiently allocated to either exploitative or explorative employees.

## **Key words**

Individual R&D performance, individual ambidexterity, internal and external resources, multi-level modelling

## **INTRODUCTION**

In much of the literature, knowledge-generation and issues related to R&D are discussed in terms of an organization's focus on either exploration or exploitation. The general conclusion is that exploration increases long-term performance by helping to generate new knowledge and, in doing so, to develop and introduce innovations, whereas exploitation maintains short-



term operational success by building on existing knowledge and extending existing products and services (Bierly and Daly 2007; Danneels 2007; March 1991; Nerkar 2003). Exploration and exploitation, however, require fundamentally different and inconsistent architectures and competencies, creating paradoxical challenges. A focus on exploration implies organizational behaviours characterized by search, discovery, experimentation, risk-taking, and innovation, while a focus on exploitation implies organizational behaviours characterized by refinement, implementation, efficiency, production, and selection (Benner and Tushman 2003; Cheng and Van de Ven 1996; March 1991).

Increasingly, organizational researchers are using ambidexterity, the ability of humans to use both hands with equal skill, as a metaphor for organizations that are equally dexterous at exploiting and exploring, and suggest that these must be balanced and intertwined for sustained performance (Raisch et al. 2009). Because both exploration and exploitation contribute to organizational survival, the literature suggests that organizations would benefit from acting ambidextrously.

Existing research on the exploration–exploitation trade-off has thus far been mainly focused on organizational-level processes, and has scarcely taken into account the individual level. In most of the studies, the tensions that ambidexterity creates are resolved at the organizational level. In sum, research has suggested that structural mechanisms are used to enable ambidexterity, whereas most individuals are seen as focused on either exploration or exploitation activities. Some studies on structural ambidexterity acknowledge that a few people at higher organizational levels need to act ambidextrously by integrating exploitative and explorative activities (e.g., Smith and Tushman 2005). However, the individual dimension of ambidexterity is not explored further (Raisch et al. 2009). It is only recently that some studies have attempted to take a step toward filling this gap empirically. Audia and Goncalo (2007) argue that greater attention should be directed to the link between individual-level processes and organizational-level processes while balancing exploration and exploitation. Mom and colleagues (2009) take this a step further, conceptualizing and measuring individual

ambidexterity for the case of managers and determining how formal structure and personal coordination mechanisms moderate such individual ambidexterity for this group. Finally, Groysberg and Lee (2009) analyze the performance implications of individual exploration and exploitation activities of professional service firms, but do not focus on the individual ambidexterity–performance relation.

Although these studies deliver valuable insights into the nature and underlying mechanisms of individual ambidexterity and lay the foundations for future research, they also serve to highlight three important deficiencies in our understanding of individual ambidexterity to date: first, to the best of our knowledge there has been no empirical investigation of ambidexterity at the R&D employee (not managerial) level; second, the performance implications of individual ambidexterity remain unclear; third, and consequently, no conclusions about the antecedents of the individual ambidexterity–performance relation can be drawn.

We feel that it is therefore crucial to develop a better understanding of whether the individual ambidexterity of R&D employees affects individual-level research performance. Since R&D employees need to cope with the dilemmas and conflicting pressures that occur when trying to balance explorative and exploitative activities (Denison et al. 1995; Smith and Tushman 2005) we further aim to shed light on the role of the complementary resources the organization can provide as moderators of the ambidexterity–performance relation. In a first step we analyze the effects of individual-level ambidexterity on individual-level R&D performance while controlling for organizational ambidexterity; in a second step we further investigate the moderation effect that resource availability exerts on this individual-level ambidexterity–performance relation. We thereby build on previous findings of ambidexterity research according to which resources play an essential role in setting the balance between explorative and exploitative activities (Cao et al. 2009; Gupta et al. 2006; March 1991). Since both types of activity compete for the same organizational resources, devoting more resources to exploitation implies that there are fewer resources left over for exploration, and vice versa (Gupta et al. 2006). Gupta and colleagues (2006) conclude that the scarcity of resources

determines the degree to which a balance between exploitation and exploration can be reached. We therefore distinguish between internal (i.e. firm) and external (i.e. network) resources, aiming to determine their moderation effect on the ambidexterity–performance relation.

Our empirical investigation is based on a sample of 332 surgeons from 20 academic medical centres (AMCs) in Germany. AMCs provide an excellent setting for research on ambidexterity because physicians working at these institutions must combine their R&D activities with daily clinical work, and are thus torn between explorative and exploitative activities. In the present study, we were able to combine three separate data sources. Individual-level R&D performance was measured by counting citations of refereed journal publications that were attributable to each surgeon and had been indexed in the ISI Web of Science. For identifying and describing internal and external resource access, we relied on self-generated survey data. The degree to which AMCs as a whole were ambidextrous was determined by using external databases. In order to increase the validity of our results, we applied rigorous methods such as data envelopment analysis (DEA) and negative binomial regression.

Our paper proceeds as follows: In Section 2, we present the conceptual background on individual ambidexterity and resource access as a relevant moderator of the ambidexterity performance relation; hypotheses are developed accordingly. Section 3 presents the research setting and sample attributes, the analytical technique applied, and the constructs used as dependent, independent, and control variables. After reporting our empirical findings in Section 4, we discuss our results, point out our study's limitations, and consider the implications for future research and management practice in Section 5.

## **THEORY AND HYPOTHESES**

### **Individual Ambidexterity**

Researchers have used ambidexterity to analyze numerous significant organizational phenomena. Its importance has been noted across the fields of strategic management (Jansen et

al. 2009; Lubatkin et al. 2006; Smith and Tushman 2005), innovation and technology management (Ambos et al. 2008; He and Wong 2004; Markman et al. 2008; Tushman and O'Reilly 1996), organizational learning and adaptation (Levinthal and March 1993), organization theory (Adler et al. 1999; Benner and Tushman 2003), and organizational behaviour (Gibson and Birkinshaw 2004).

Despite the increasing interest in ambidexterity as a concept, an examination of the literature indicates that several important research issues remain unexplored, ambiguous, or conceptually vague. In fact, there have been several calls recently for more integrative and multilevel analyses of ambidexterity (e.g. Gupta et al. 2006; Jansen et al. 2009; Raisch et al. 2009; Simsek 2009) as well as a more comprehensive analysis of the interrelationships between different antecedents of ambidexterity and the complexity of the ambidexterity–performance relationship (Raisch and Birkinshaw 2008). One of the major shortcomings in this sense has been the lack of a micro-foundation for ambidexterity, although first attempts towards a conceptualization and micro-analysis of individual ambidexterity have been made (Audia and Goncalo 2007; Bledow et al. 2009; Groysberg and Lee 2009; Mom et al. 2009).

In order to advance the existing models of individual ambidexterity it is important to distinguish organizational from individual ambidexterity. Simsek (2009) refers to organizational ambidexterity as *realized* ambidexterity, understood in terms of the organization's exploitation and exploration attainments. Thus organizational ambidexterity explicitly focuses on the organization's current exploration and exploitation performance, while structural and contextual ambidexterity describe settings or behaviours that enable and/or result in ambidexterity. Simsek (2009) further summarizes the key elements of ambidexterity in what he refers to as an 'input–process–output' view, which consists of the antecedents of ambidexterity (e.g. structural or contextual elements of ambidexterity), the components of ambidexterity (processes, e.g. exploration and exploitation) and lastly the outcomes of ambidexterity (outputs, e.g. financial performance).

Structural elements of ambidexterity might consist of structures and strategies to enable differentiation. Such differentiation tactics help manage bounded rationality by ensuring focus, but may engender isolation, engrain a preferred innovation mode, and impede coordination between varied efforts (Gibson and Birkinshaw 2004). Contextual ambidexterity utilizes more behavioural and social means to integrate exploitation and exploration. Lubatkin and colleagues (2006) theorize that greater behavioural integration helps one to cope with the contradictory knowledge processes of exploitation and exploration and enable their joint pursuit. Gibson and Birkinshaw (2004) present contextual ambidexterity as a higher-order approach. Supportive social processes (e.g. socialization and recognition practices), culture, and interpersonal relations help actors throughout the firm think and act ambidextrously. Ghoshal and Bartlett (1997) depict context as the largely invisible set of stimuli and pressures that can shape individual and collective behaviours toward ambidexterity.

On the other hand, Bledow and colleagues (2009) find that balancing explorative and exploitative activities is not only a challenge for the upper echelon of an organization but a phenomenon that goes beyond structural and contextual mechanisms and spans all levels of an organization. Individual employees, collectives of employees such as work teams, and the organization as a whole have to find strategies to deal with conflicting demands in order to successfully innovate and adapt to changing markets. Consequently, a thoroughly conceptualized model of individual ambidexterity requires a multi-level approach, taking into account the organizational level and its necessary mechanisms to enable individuals to act ambidextrously.

In keeping with the terminology in use with respect to the organizational level, we propose that ‘ambidexterity’ at the individual level be used to refer to the actual ability of individuals to excel at both exploration and exploitation, which must be complemented and enabled by the appropriate structural and behavioural antecedents of ambidexterity at the organizational level.

### **Individual Ambidexterity and R&D Performance**

Although empirical research on the outcomes associated with ambidexterity is abundant, its results have been complex – and mixed. The implicit premise of March’s (1991) ‘balance hypothesis’ is that organizations attain superior performance by pursuing both exploration and exploitation, instead of trading off one activity for the other. This premise is made explicit in ambidexterity research (e.g. Tushman and O’Reilly 1996). Although some researchers have found that ambidexterity directly impacts performance (e.g. Gibson and Birkinshaw 2004; He and Wong 2004; Lubatkin et al. 2006), others have found a contingent effect (e.g. Lin et al., 2007, where the effect is found to be contingent on organizational size), and some a negative effect (e.g. Atuahene-Gima 2005). More recent studies (Uotila et al. 2009; Yang and Atuahene-Gima 2007) find evidence that ambidexterity is curvilinearly related to performance, while another finds no support for the ambidexterity hypothesis (Venkatraman et al. 2006). Moreover, other studies have considered the performance implications of exploitation and exploration, rather than ambidexterity per se (e.g. Auh and Menguc 2005; Jansen et al. 2006). In summary, the ambidexterity literature has only provided anecdotal empirical evidence of the positive performance implications of ambidexterity (Lavie et al. 2010). While there is empirical evidence – albeit scarce – for a positive ambidexterity–performance relation at the organizational level of analysis, there is no empirical analysis to date that investigates how individual performance is affected by ambidextrous behaviour.

Recent psychological research on the antecedents of individual creativity and innovation has, however, provided conclusions that would justify the assumption of a positive relation between individual R&D performance and individual ambidexterity. Hirst and colleagues (2009) find that individual creativity benefits from combining and balancing antipodal activities such as learning orientation (exploration) and goal orientation (exploitation). Gilson and colleagues (2005) have demonstrated that creativity and standardization – creativity being explorative and standardization exploitative – can not only co-occur within work teams, but actually interact to bring about superior performance. Bledow and colleagues (2009) propose that innovation

requires the regulation of exploration and exploitation and their antecedents (e.g. divergent and convergent thinking, learning and performance orientation). Exploitative activities and expertise provide the fundamentals for continuous improvement but need to be challenged by explorative activities for new ideas to emerge. New ideas that emerge, in turn, require exploitative activities to be successfully implemented (Bledow et al. 2009). Finally, Smith (2009) also proposes that engaging with contradictions simultaneously enables increased creativity, flexibility, and long-term success. With these observations in mind, we put forward our first hypothesis.

*Hypothesis 1: Individual ambidexterity increases individual R&D performance.*

### **Resources and their Role as Moderators of the Ambidexterity–Performance Relationship**

The overall strategic emphasis of an organization is reflected in investments of resources in activities and processes that promote exploration or exploitation (Siggelkow and Levinthal 2003). Because exploration and exploitation represent very different organizational processes, they may each require different sets of supporting resources in order to impact performance positively (March 1991). The exploitative units need to mobilize information and knowledge within the firm to improve the efficiency of existing organizational routines (Benner and Tushman 2003; March 1991), whereas the exploratory units need to get detached from the existing routines and engage in more scanning of the information and knowledge that resides outside the firm (McGrath 2001). This leads to the conclusion that different resource types affect explorative and exploitative activities and their respective outcomes in varying ways. With respect to this, Cao and colleagues (2009) propose that at the level of the firm the nature of the ambidexterity–performance link is contingent on the availability of different resource types, where resources are divided, roughly, into those that an organization possesses and those it can access from outside its own boundaries – in other words, internal and external resources.

According to the resource-based view (Eisenhardt and Martin 2000), the size of a firm's resource base can be seen as the fundamental determinant of organizational performance (Barney 1991). On the other hand, it is a persistent theme in the literature that organizations and their employees are embedded in networks of relations (Pfeffer and Salancik 1978), and this is especially the case for organizations coping with a high level of complexity (Yang and Lin 2010). These external resources allow the firm to accumulate and exchange knowledge, to gather new ideas and to identify opportunities (Burt 1992; Granovetter 1985). According to social network theory, networks spanning social divides are associated with performance-related outcomes (Burt, 1992). However, networks might also have unintended consequences for performance if they result in comfortable or validating interactions but do not deliver the most relevant knowledge for the task at hand (Erickson 1988; Mizruchi and Steams 2001).

Thus, access to internal and external resources may both facilitate and impede R&D performance. However, it has not yet been subject to analysis how internal and external resources affect the R&D performance of individuals who have to balance exploration and exploitation in their daily work. In order to close this research gap, we apply the internal/external resource distinction to our model of individual ambidexterity and investigate how access to internal and external resources moderates the individual ambidexterity–performance relation.

### ***Internal Resources***

Organizational scholars have long argued that exploration and exploitation are fundamentally different activities and that independent or even conflicting determinants, such as personality or goal orientations, influence performance of the respective activities (e.g. Farr et al. 2003; Farr and Ford 1990; Kimberly and Evanisko 1981). Thus, the pursuit of ambidexterity poses fundamental problems for the self-regulation of individuals who aim to bring about new ideas while at the same time implementing and applying both new ideas and existing knowledge in a given organizational setting. The creation of new ideas is an exploratory activity that is based



on divergent processes and leads to increases in variability. In contrast, implementation activities are based on convergent processes aimed at exploiting the potential value of new and existing ideas and leading to a reduction of variability (Bledow et al. 2009). When an organization becomes committed to a new idea, its activities need to converge around the implementation of that idea.

To comply with the complexity of combining these diverging activities requires adequate organizational support (O'Reilly and Tushman 2008) – support that is not only limited to funding, time, and labour, but also to senior management support. We refer to this support as internal resources. Thus, we argue that success at pursuing ambidexterity will depend on the extent to which sufficient internal resources can be accessed and allocated to support a high level of engagement in exploration and exploitation. As a consequence, we reason that when an individual has access to a larger stock of internal resources, he or she can cope with the demands of balancing exploratory and exploitative efforts and that those activities will be carried out more effectively, leading to an increase in individual R&D performance. Based on these assumptions we formulate our second hypothesis as follows.

*Hypothesis 2: Internal resource access will positively affect the relationship between individual ambidexterity and individual R&D performance.*

### ***External Resources***

Access to external resources might considerably ease the constraints imposed on organizations (and individuals) by the scarcity of internal resources (Gupta et al. 2006). In other words, this means that when organizational support as described above cannot be granted internally for whatever reason, organizations or individuals might benefit from obtaining some of the missing support through external partners. Besides physical support through funding and technology, they might help to apply the right information to solve novel and challenging problems. In information search, external resources increase the diversity of available knowledge and the access to complementary partners for R&D (Reagans and McEvily 2003).

The direct link between external resources and individual R&D performance can therefore be assumed to be positive. This holds true for individuals who focus on exploration as well for their exploitative colleagues. Both may add to relevant competences and physical resources which are not available elsewhere. Exploitative team members may compensate for missing research-oriented competences and explorative employees can add knowledge necessary for implementation.

Given the cognitive and behavioural complexity described by ambidexterity, however, we assume that it is questionable whether individuals are able to the same extent to transform the acquired external support and knowledge into new ideas and/or products. We see three arguments for this proposition. (1) An intensive access to external networks adds to the complexity individuals have to cope with. Ambidextrous individuals must switch between different mind and action sets in accordance with situational demands. For instance, individuals must carefully elaborate and weigh the advantages and disadvantages of different courses of action, and, once a decision is made, switch to a mode of information-processing that is focused on acting to achieve a specific goal (Gollwitzer et al. 1990). The diversity of external partners and the uncertainty of dealing with new partners imply that coordination and information-processing demands increase, and as the external resources have to be embedded into exploitative and explorative tasks the complexity will be disproportionately high. (2) Ambidextrous employees have to deal with diverse tasks and therefore are likely to be characterized by high diversity and multiple competences. External networks should compensate for missing knowledge, and therefore ambidextrous employees might benefit less from external resources. (3) Building and maintaining external networks takes time, which competes with the time necessary for combining exploitation and exploration. The challenge in this situation arises because exploitative activities are very often mandatory and urgent, and therefore the time for using external resources will most likely be taken at the expense of exploration. Hence, when ambidextrous individuals are too involved in developing and

cultivating their networks they might not be able to effectively pursue both explorative and exploitative activities. This leads to the third hypothesis of our study.

*Hypothesis 3: External resource access will negatively affect the relationship between individual ambidexterity and individual R&D performance.*

## **METHODS**

### **Setting and Data**

In order to analyze the influence of individual ambidexterity on individual-level R&D performance, it is vital to choose a setting where research activity can be traced back to individual employees. Unlike R&D firms, universities are a good example of such a setting because individual-level R&D performance can be measured in terms of publication output and the publications themselves can be attributed to individual authors (van Rijnsoever et al. 2008). At least some scientific fields (e.g. medicine) have developed standardized publication measures and use them as performance indicators. Our empirical investigation is thus based on a sample of surgeons working at AMCs in Germany. In contrast to other hospitals, AMCs are usually part of a university or medical school, and their mission to combine patient care (i.e. exploitation) and research (i.e. exploration) often leads to a trade-off between these two goals, reducing overall performance (Schreyögg and von Reitzenstein 2008). AMCs are thus perfectly suited for analyzing ambidexterity. Out of all medical fields, we chose the field of surgery for our analysis because surgeons require exceptionally specialized technological expertise as well as abundant resources for both patient care and research. Furthermore, the potential conflicts between exploitative and explorative activities are most prevalent in surgery, where the daily operational work is to a high degree manual and based on experience.

In total, we surveyed 332 surgeons in twenty AMCs using a self-designed questionnaire based on five-point Likert scales. During the preparatory phase of the study, we distributed a preliminary version of the questionnaire to twenty-five surgeons of various subspecialties (e.g.

general surgery, surgical oncology, cardiothoracic surgery), who subsequently provided us with feedback which was used to refine the final survey instrument.

We contacted all 33 German medical schools, 20 of which agreed to participate in the survey. In these 20 medical schools we distributed our paper-based questionnaire to approx. 700 surgeons. 371 surveys were completed, which corresponds to a response rate of 53%. Of these responses, 8 had to be excluded due to missing data, resulting in a total of 363 useable questionnaires. Subsequently, data from the survey were combined with objective data on participating surgeons' R&D performance, which we measured by counting citations of refereed journal publications that were attributable to each surgeon and had been indexed on the ISI Web of Science. Because 31 surgeons had not included their names on the questionnaire, data on a total of 332 surgeons were ultimately included in our analysis.

Of these surgeons, 269 were men and 63 were women, and the mean age of the sample was 38 years. We divided the sample into four subgroups according to subspecialty, assigning 184 to the general surgery group (SURG; including transplant surgery and surgical oncology), 77 to the orthopaedic surgery group (ORTHO; including trauma surgery), 36 to the cardiothoracic surgery group (CARDIAC), and 35 to the miscellaneous subspecialties group (OTHER; including neurological, plastic, paediatric, ophthalmological, urological, head and neck, gynaecological, and otolaryngological surgery).

## **Measures**

### ***Individual R&D Performance***

Although indicators such as technology licenses have recently attained prominence in innovation research (Chang et al. 2009; Nelson 2009; Powers and McDougall 2005), patents and publication citations have remained the indicators of choice. We focus on publication citations because they represent an essential part of virtually any academic career in medicine and the natural sciences (Dundar and Lewis 1998; Neill 2008; Olson 1994). While publication

counts are a valid proxy for research activity, citations are increasingly viewed as a measure of research quality (He et al. 2009). We therefore used total citation counts as the dependent variable to proxy for the R&D performance of each participating surgeon. Due to the lack of standardized authorship conventions that would have allowed us to estimate the extent of a surgeon's contribution to each paper, we decided to use the total citation count regardless of the position at which a surgeon's name appeared in the author list for a paper. Citation records were obtained from the ISI Web of Science, which covers more than 10,000 journals from over 100 scientific disciplines. Because the errors inherent in electronic databases necessitate stringent quality-control procedures (Hood and Wilson 2003), we identified participating surgeons by matching their departments and institutions in addition to their names. To reduce age biases and to increase robustness, we selected a six-year period (2005 through 2010), counting all articles in which the participating surgeons appeared as authors.

### ***Individual Ambidexterity***

To conceptualize individual ambidexterity we follow the suggestions by Gupta and colleagues (2006) that if the premise is that exploration and exploitation are orthogonal and not mutually exclusive then the correct test for the beneficial effects of balance would be to test for positive interaction effects between both activities. To conceptualize exploration we asked surgeons to indicate the percentage of their working time spent on research (survey question: 'Please indicate the percentage of your working time that you devote to research activities'), whereas to model exploitation we asked surgeons to indicate the amount of working time they devote to clinical tasks (survey question: 'Please indicate the percentage of your working time that you devote to medical care'). Individual ambidexterity is finally calculated by multiplying both percentages.

***Internal and External Resources***

In our survey, we analyzed access to internal and external resources using five-point Likert scales with items ranging from (1) ‘strongly disagree’ to (5) ‘strongly agree’. Two distinct factors were identified through exploratory factor analysis. Results from a confirmatory factor analysis indicated adequate fit for our measures of internal and external resources as defined by Hu and Bentler (1998) (GFI = .92, SRMR = .072, RMSEA = .08, CFI = .92). The first factor, which we refer to as ‘internal resources’, expresses the degree to which surgeons have access to internal resources. We asked surgeons to specify the extent to which (1) ‘[their] hospital provides them with sufficient funding to innovate’ [.79], (2) ‘[they] have sufficient specialist staff supporting innovative activities’ [.80], ‘[they] have sufficient administrative staff (e.g. study office) supporting innovative activities’ [.75], (4) ‘[they] have sufficient access to technological and laboratory equipment’ [.69], (5) ‘[they] have sufficient top-level support’ [.82], and (6) ‘the organizational culture of [their] institution encourages innovative behaviour’ [.66]. The six items loaded on a single factor, having only one eigen value greater than 1 and accounting for 29 % of the variance ( $\alpha = .85$ ).

The other factor, which we refer to as ‘external resources’, represents participating surgeons’ activity in external networks and their usage of out-of-their-domain contacts. To capture external resource access, we asked surgeons to indicate the extent to which (1) ‘[they] frequently exchange ideas with colleagues outside [their] hospital’ [.70], (2) ‘[they] know the right people outside [their] hospital who could support [them] in the pursuit of innovative projects’ [.66], (3) ‘[they] talk to manufacturer’s representatives’ [.78], (4) ‘[they] talk to engineers’ [.71], and (5) ‘[they] visit exhibitions that present new medical technologies’ [.73]. The five items loaded on a single factor, having only one eigen value greater than 1 and accounting for 26 % of the variance ( $\alpha = .76$ ).

### ***Control Variables***

To reduce the likelihood of unobserved heterogeneity among surgeons, we controlled for several attributes. First, we controlled for ambidexterity at the organizational level. Data to model organizational measures of exploration and exploitation were collected at the AMC level by using external databases such as the Centrum fuer Hochschulentwicklung (CHE) report (CHE Centrum fuer Hochschulentwicklung 2006), a detailed ranking of German institutions of higher education, and the ISI Web of Science. To model the variable ‘organizational exploration’, we used the ISI Web of Science to determine publication counts for all department members during the same five-year period (i.e. 2004 through 2008); the average number of publications per head and department in each AMC serves as a proxy for a focus on exploration. In turn, the variable ‘organizational exploitation’ represents the technical efficiency of an AMC with respect to the delivery of patient care, with high efficiency serving as a proxy for a focus on exploitation. Efficiency scores were calculated using data envelopment analysis (DEA), which is described in more detail below. Because surgeons who completed the survey were also included in the average publication measures, we performed sensitivity analyses, excluding survey respondents from mean calculations to address potential endogeneity issues. Organizational ambidexterity was finally operationalized in the same way as for individual ambidexterity by calculating the interaction term between previously standardized exploration and exploitation scores. Further, we looked for differences between the surgeons’ subspecialties, specifically the groups SURG, ORTHO, CARDIAC, and OTHER as defined in the previous section. Lastly, we controlled for age to reduce career-stage biases.

### **Empirical Model**

Our empirical model is based on the assumption that the R&D performance of surgeons is a function of individual surgeon characteristics and attitudes, as well as of the general strategies followed by AMCs, which are determined by hospital management. It is important to recognize that whereas individual characteristics and attitudes may differ from surgeon to

surgeon, AMC strategies apply to all surgeons employed at a given AMC. As a result, observations across surgeons are not independent. This intra-class correlation violates classical OLS assumptions such as independence and common variance. Moreover, standard errors for AMC-level effects are likely to be underestimated with OLS. Significance tests would therefore lack robustness, overestimating the precision of information provided by the AMC-level variables (Kreft and De Leeuw 1998; Snijders and Bosker 1999). To avoid this problem, we applied multi-level modelling. The structure of multi-level modelling has been described in detail by Gupta and colleagues (2007) and Hitt and colleagues (2007). In our study, we took a multi-level modelling approach with two levels, nesting surgeons as micro units within hospitals, which were, in turn, considered to be macro units. We used the following model

$$y_{ij} = \beta_{0j} + \beta_1 x_{ij} + \beta_2 z_j + \varepsilon_{ij}$$

$$\beta_{0j} = \beta_0 + u_j$$

where  $y_{ij}$  is the dependent variable, representing the  $i$ th surgeon's R&D performance. The intercept for the  $j$ th AMC is given here as a fixed component  $\beta_0$  and a random component  $u_j$ , which indicates the random effects among AMCs on the dependent variable. Moreover,  $x_{ij}$  is a vector of explanatory variables at the surgeon level and represents individual ambidexterity, and internal and external resources as well as the control variables, whereas  $z_j$  is a vector of explanatory variables at the hospital level that represents organizational ambidexterity. The random term  $\varepsilon_j$  represents the unexplained variation for surgeons within an AMC. The random terms  $u_j$  and  $\varepsilon_j$  are assumed to be normally distributed with zero mean. We grand-mean-centred all independent and control variables to facilitate interpretation of moderation effects (Aiken et al. 1991).

The dependent variable in the present analysis – namely publication citations – is a non-negative, integer count variable. When choosing an appropriate empirical model to examine the impact of our covariates on the R&D performance of surgeons, we had to consider that the distribution of our dependent variable was skewed strongly to the right and contained a



substantial proportion of zeros. Several estimation techniques have been proposed in the literature to deal with distributional characteristics like these, including Poisson and negative binomial (NB) models, as well as zero-inflated Poisson (ZIP) and zero-inflated negative binomial (ZINB) models (Yau et al. 2003). To determine the best fit among ZINB, ZIP, NB, and Poisson, we followed the steps proposed by Greene (1994) and Chou and Steenhard (2009).

As verified by a statistical test for overdispersion (Gourieroux et al. 1984), the negative binomial estimation provided a significantly better fit for the data than the more restrictive Poisson model. To find the better fit between NB and ZINB, we applied the Vuong test (Vuong 1989), which compares the conditional models with the true conditional distribution, to determine whether NB should be rejected in favour of ZINB. For both dependent variables, the results of the Vuong test suggested that the NB and ZINB models were equally efficient. Because other common criteria of fit, such as Akaike's information criterion (AIC) and the Bayesian information criterion (BIC), also indicated that NB was superior in this regard, we chose to use this model throughout our analysis.

### **Data Envelopment Analysis (DEA)**

To determine the relative efficiency of patient care, we employed DEA – the most frequently used approach to measuring efficiency in the hospital sector (Hollingsworth 2003). As a linear programming technique for evaluating the relative efficiency of individual organizations based on observed data, DEA allows multiple inputs and outputs to be considered simultaneously (Cooper et al. 2004), which is particularly well-suited for measuring the efficiency of hospitals. In the present study, we used an input-oriented DEA approach to address the following question: ‘To what extent can the input factors, defined as supplies and labour, be reduced proportionally without changing the output quantities of hospitals, defined as the number of cases?’ When selecting inputs and outputs, we followed the example of other studies that have developed DEA frameworks for measuring hospital efficiency (Burgess Jr

and Wilson 1996; Pilyavsky et al. 2006). In total, we considered five inputs and one output. The first input variable is the amount spent on supplies per year, including operational expenses but excluding payroll, capital, and depreciation expenses. Taking into account the importance of labour resources in the hospital production process, we included the number of full-time equivalents for the following personnel categories as additional input variables: total medical faculty, nursing staff, technical staff, and other staff members. The output variable reflects the number of treated inpatient cases per year in all hospitals associated with each AMC.

## RESULTS

Table 1 shows our descriptive statistics and bivariate correlation matrix, while Table 2 presents the results of our regression analysis. The surgeons were well distributed across the various subspecialties, represented a broad range of ages (26–61 years), and included individuals who were very innovative and those who were not. The goodness-of-fit tests indicated that the chosen model fit the data very well.

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Please insert Table 1 about here

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We began by estimating a baseline model with individual- and organizational-level variables, as well as control variables. The subsequent model included interaction terms to explore whether internal and external resources have moderating effects on the relationship between individual ambidexterity and individual R&D performance. We performed Wald tests for the null hypothesis, which states that the parameters of the models with interaction effects do not differ from those of the models without interaction effects (i.e. the parameters of the squared variables are assumed to be zero). Because the chi-square statistic indicated strong significance ( $P < 0.001$ ) for the former compared to the latter models, the parameters of the interaction variables could not be assumed to be zero and the null hypothesis had to be rejected.

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Please insert Table 2 about here

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Our analysis reveals the following results: Internal as well as external resources have a positive impact on individual R&D performance ( $P < 0.001$ ). Surgeons who have sufficient access to internal and external resources tend to have a strong individual research performance. Individual research performance also benefits from an individual exploration orientation ( $P < 0.001$ ) while no significant conclusions can be drawn from an individual exploitation orientation.

Our first hypothesis (H1) suggested that individual ambidexterity has a positive impact on individual R&D performance. Our data provided significant support ( $P < 0.001$ ) for this proposition, indicating that individual ambidexterity – modelled as the interaction of individual exploration and individual exploitation – stimulates individual R&D performance.

Further, our second hypothesis (H2) suggested that internal resource access positively influences the relationship between individual ambidexterity and individual R&D performance. This hypothesis was supported by our data with  $P < 0.001$ . When internal resource access is provided, surgeons with a high degree of individual ambidexterity have a strong R&D performance. On the other hand it has to be acknowledged that exploration-oriented surgeons cannot transform internal resources into R&D output, while exploitation-oriented surgeons benefit from vast access to internal resources ( $P < 0.001$ ).

Lastly, we proposed in hypothesis 3 (H3) that external resource access negatively influences the relationship between individual ambidexterity and individual R&D performance. This hypothesis was also supported by our data. External network access has a significant negative three-way interaction effect ( $P < 0.001$ ) between individual ambidexterity and individual R&D performance. Ambidextrous surgeons who are very active in external networks have a weaker R&D performance than ambidextrous surgeons who rely solely on internal resources. However, focused exploration-oriented individuals clearly benefit from network activity ( $P <$

0.001). No significant conclusions can be drawn about the effect of external resources on the R&D performance of exploitation-oriented individuals.

We checked the robustness of our results in several ways. First, we tested alternative count data specifications, including Poisson and ZINB models. The modifications had very little impact on the coefficients, and all effects remained significant. Second, we re-estimated the models by using publication and citation counts for the years 2008 through 2010 only, thus addressing concerns that publication activity may not have resulted directly from the strategies examined by our questionnaires, or that strategies may have changed over time. Importantly, coefficients did not change their direction, and the level of significance changed only marginally throughout the estimations. Third, we tested alternative dependent variables such as total publication counts. The results remained stable although the coefficients slightly lost significance. Fourth, we ran models excluding resident surgeons to control for a potential age and experience bias, as resident surgeons might not have the necessary experience and time to publish. The results slightly lost significance but the direction of the main effects remained the same. Finally, we modified the variable ‘organizational exploration’ by excluding survey respondents from the measure ‘publications per faculty’ to minimize bias, and subsequently re-estimated the models. Again, our results remained robust. We therefore believe that the findings of our study are valid and reliable.

## **DISCUSSION**

In the present study, we explored the individual-level R&D performance of 332 surgeons at twenty AMCs in Germany and the influence exerted upon it by individual ambidexterity. In a second step, we investigated how this individual ambidexterity–performance relation is moderated by access to internal and external resources; we thereby controlled for organizational ambidexterity at the AMC level. Ambidexterity on both levels was operationalized as combined ambidexterity – in other words, the simultaneous pursuit of both explorative as well as exploitative activities.

This study makes several contributions. From a conceptual point of view our study responds to the call for a micro-perspective on trade-offs between exploration and exploitation at the individual level. By means of a conceptualization of individual ambidexterity – while controlling for organizational ambidexterity – we complement and extend the existing models of individual ambidexterity (e.g. Mom et al. 2009). Second, by analyzing how individual-level R&D performance is affected by such individual ambidexterity we add to the literature regarding the performance effects of individual ambidexterity. Third, we present insights into the underlying moderation effects of the individual ambidexterity–performance relationship. Lastly, the advantages of multi-level methods allowed us to develop a framework to control for ambidexterity at the organizational level.

We found that individual ambidexterity had a positive impact on individual-level R&D performance. Individuals who combine explorative with exploitative tasks perform well in their research efforts. This finding confirms suggestions by previous creativity and innovation research that creativity benefits from the coexistence of characteristics that may seem incompatible from a dichotomous perspective but which hold a functional value for innovation (Bledow et al. 2009). Examples of such dichotomies include attention to detail and innovativeness (Miron et al. 2004), conscientiousness and openness to experience (George and Zhou 2001), as well as systematic versus intuitive problem-solving styles (Scott and Bruce 1994). The positive impact of balancing individual explorative and exploitative activities has, however, not yet been tested empirically, although it has long been proposed, beginning with March (1991), that individuals who balance the dual requirements of searching for new knowledge (exploration) and the application of this knowledge (exploitation) were better at developing solutions to applied problems than individuals who overemphasize learning.

We further hypothesized that internal resources positively moderate this relation while external resources have a negative impact. Both hypotheses could be supported by our data. Internal resources indeed stimulate, while external resources weaken the individual ambidexterity–performance relation. The R&D performance of individuals who simultaneously pursue

explorative and exploitative activities thus benefits from sufficient access to internal resources. This finding corroborates conclusions made by Cao and colleagues (2009) that managers in resource-constrained contexts may benefit from a focus on managing trade-offs between exploration and exploitation demands. Consequently, it is both possible and desirable for firms that have sufficient access to resources to simultaneously pursue exploration and exploitation activities. Gupta and colleagues (2006) also emphasized that resources which are typically scarce, such as internal resources, are key to the simultaneous pursuit of exploration and exploitation. The data clearly show that individuals who can successfully combine these activities need appropriate internal support and resources.

Although one might argue that the challenges for individuals who work in complex jobs – such as those with ambidextrous work requirements – might lead them to draw upon external resources to be creative, our data showed that ambidextrous individuals who are very active in external networks are apparently not able to effectively transform these external resources into R&D output. This is an interesting finding, since the major part of the literature has identified external resources as an opportunity to overcome internal resource constraints (e.g. Gupta et al. 2006). However, the situation might be different in an ambidextrous setting where job complexity and work load are very high. In keeping with Gupta and colleagues' (2006) scarcity argument, we may say that external resources are not scarce; rather, they are infinite. When resources are infinite the consumer runs the risk of information overload, especially when job complexity is high.

In summary, our data indicates that internal resources stimulate and external resources impede the R&D performance of ambidextrous individuals. In order to interpret these findings accurately it is vital to look at the impact that internal and external resources exert on the R&D performance of exploration- and exploitation-oriented individuals. The R&D performance of exploration-oriented surgeons benefits from access to sufficient external, but suffers from internal resources, while performance of exploitation-oriented individuals – on the contrary – benefits from internal resources.

Our study has a number of important limitations. Chief among these is our use of citation counts as the sole measures of R&D output. Analyzing journal articles is fraught with difficulties related to authorship, journal quality, and publication type. Although our analysis does not differentiate between articles based upon the order of authorship, we initially considered the number of articles with first authorship as a dependent variable. Doing so resulted, however, in a sample that was too small for statistical evaluation. Future studies on similar topics might benefit from including additional measures of R&D output, such as patent counts. Unfortunately, using patent counts was not a solution in our case, as a search in our sample using the PATSTAT 2009 database revealed that 225 patents had been filed by 34 surgeons, which also would have been too small for meaningful study. Another shortcoming is related to the issue of journal quality, although citation counts allowed for some quality assessment because higher-ranked journals (and, generally, higher-quality research) are presumably cited more frequently.

Additionally, although we found that AMCs were a suitable environment for testing our hypotheses, the present study's focus on medical, and particularly on surgical, research raises questions about the generalizability of our findings. Academic physicians are unique in their triad of patient care, research, and teaching duties. We are nevertheless convinced that our results can be transferred to other functional backgrounds and industry sectors because previous studies have also successfully used hospital-based surgical settings to analyze organizational phenomena and individual-level performance issues (Gittell et al. 2010; Huckman and Pisano 2006; Pisano et al. 2001).

In conclusion, many studies suggest that resolving the conflict between exploration and exploitation can improve organizational performance by delivering the efficiencies inherent in intense exploitation without sacrificing adaptability – in other words, combining steady exploitation with vibrant exploration (Gibson and Birkinshaw 2004; March 1991). In order to achieve this goal, managerial attention would be directed to the individual level as well as to the organizational level. Our findings show that individual ambidexterity may increase

individual-level R&D performance, thus leading to an increase in an organization's overall R&D performance. R&D managers should consequently ensure that the creative workforce acts ambidextrously, and thus is not only engaged with explorative tasks but also involved in exploitative activities. Further, managers should make sure that appropriate resources are provided to individuals who attempt to combine exploration and exploitation. Ambidextrous individuals benefit most from internal resources that are usually scarce, while their research efforts can suffer if they have too much access to external resources, e.g. are too active in external networks.

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Table 1. Descriptive statistics and bivariate correlation matrix

Variable	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10	11
1 Citations	57.02	129.58	0.00	1737.00	-										
2 Internal resources	2.66	0.86	1.00	5.00	0.12	-									
3 External resources	3.18	0.79	1.00	5.00	0.22	0.15	-								
4 Individual exploration	9.25	8.72	0.00	90.00	0.19	0.14	0.22	-							
5 Individual exploitation	49.57	18.61	0.00	100.00	0.07	-0.05	0.16	-0.21	-						
6 Age	37.92	7.74	26.00	61.00	0.26	-0.21	0.36	0.15	0.17	-					
7 Surg	0.55	0.5	0.00	1.00	0.13	0.08	-0.13	0.05	-0.01	-0.11	-				
8 Cardiac	0.11	0.31	0.00	1.00	0	-0.04	0.08	0.03	0.08	0.05	-0.39	-			
9 Ortho	0.23	0.42	0.00	1.00	-0.14	-0.01	0.02	-0.08	-0.08	-0.11	-0.61	-0.19	-		
10 Other	0.11	0.31	0.00	1.00	-0.01	-0.07	0.1	-0.01	0.04	0.27	-0.38	-0.12	-0.19	-	
11 Organizational exploration	7.35	2.61	4.56	13.31	0.17	0.16	0.13	0.06	0.02	0.01	-0.05	0.04	-0.04	0.11	-
12 Organizational exploitation	0.89	0.14	0.68	1.13	0.17	0.07	0.15	0.1	0.07	0.17	-0.13	0.09	-0.08	0.22	0.45

*n* = 332; All correlations above |0.10| are significant at *P* < 0.05

Table 2. Results of the random-effects negative binomial regression

Variable	Citations	
	Model 1	Model 2
Intercept	3.88***	3.81***
<i>Main effects</i>		
Internal resources	0.15***	0.24***
External resources	0.28***	0.63***
Individual exploration	0.03***	0.05***
Individual exploitation	0.01***	-0.003
Individual ambidexterity (H1) [= Individual exploration × individual exploitation]		0.003***
Individual exploration × internal resources		-0.04***
Individual exploitation × internal resources		0.003***
Individual ambidexterity × internal resources (H2)		0.0004***
Individual exploration × external resources		0.02***
Individual exploitation × external resources		-0.0006
Individual ambidexterity × external resources (H3)		-0.001***
<i>Controls</i>		
Age	0.06***	0.06***
Surg (Reference)	0.0	0.0
Cardiac	-0.10***	-0.21***
Ortho	-0.93***	-0.97***
Other	-0.97***	-0.74***
Organizational exploration	0.08***	-0.26***
Organizational exploitation	-0.42***	-2.08***
Organizational ambidexterity [= Organizational exploration × organizational exploitation]		0.34***
<i>Fit statistics</i>		
Log likelihood	-14142.32	-13353.28
LR chi-square (DF)	10860.84 (10)	12438.92 (17)
Improvement (Wald test; Chi2 (4))		1578.08***
Comparison		Model 1

*n*=332 Note: Results are presented on the log scale because we used a log link function.

\* *P*<0.05

\*\* *P*<0.01

\*\*\* *P*<0.001

## EIDESSTATTLICHE ERKLÄRUNG

Hiermit erkläre ich, Constantin von Reitzenstein, an Eides statt, dass ich die Dissertation mit dem Titel

**“Antecedents of individual research performance of surgeons”**

An empirical analysis of surgeons in US and German Academic Medical Centers

selbständig und ohne fremde Hilfe verfasst habe.

Andere als die von mir angegebenen Quellen und Hilfsmittel habe ich nicht benutzt. Die den herangezogenen Werken wörtlich oder sinngemäß entnommenen Stellen sind als solche gekennzeichnet.

Hamburg, den 15.04.2010

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(Constantin von Reitzenstein)